Human Data Model: Improving Programmability of Health and Well-Being Data for Enhanced Perception and Interaction

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2020-09

Mäkitalo , N , Flores-Martin , D , Flores , H , Lagerspetz , E , Christophe , F , Ihantola , P , Babazadeh , M , Hui , P , Murillo , J M , Tarkoma , S & Mikkonen , T 2020 , ' Human Data Model: Improving Programmability of Health and Well-Being Data for Enhanced Perception and Interaction ' , ACM Transactions on Computing for Healthcare , vol. 1 , no. 4 . https://doi.org/10.1145/3402524

http://hdl.handle.net/10138/322899
https://doi.org/10.1145/3402524

other

Human Data Model: Improving Programmability of Health and Well-Being Data for Enhanced Perception and Interaction

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Today, an increasing number of systems produce, process, and store personal and intimate data. Such data has plenty of potential for entirely new types of software applications as well as for improving old applications, in particular in the domain of smart healthcare. However, utilizing this data, especially when it is continuously generated by sensors and other devices, with the current approaches is complex – data is often using proprietary formats and storage, and mixing and matching data of different origin is not easy. Furthermore, many of the systems are such that they should stimulate interactions with humans, which further complicates the systems. In this article, we introduce Human Data Model (HDM) – a new tool and a programming model for programmers as well as end-users with scripting skills that help to combine data from various sources, to perform computations, and to develop and schedule computer-human interactions. Written in JavaScript, the software implementing the model can be run in almost any computer either inside the browser or using Node.js. Its source code can be freely downloaded from GitHub, and the implementation can be used with the existing IoT platforms. As a whole, the paper is inspired by a number of interviews with professionals, and an online survey among healthcare and education professionals, where the results show that the interviewed subjects almost entirely lack ideas on how to benefit the ever-increasing amount of data measured of the humans. We believe that this is because of the missing support for programming models for accessing and handling the data, which can be satisfied with the Human Data Model.

CCS Concepts: • **Information systems → Data management systems**; • **Software and its engineering → Distributed systems organizing principles**; **Software design techniques**; • **Human-centered computing** → *Human computer interaction (HCI)*; *Ubiquitous and mobile computing*; • **Computer systems organization** → *Distributed architectures*; Embedded systems.

Additional Key Words and Phrases: Mobile Computing, Ubiquitous Computing, Pervasive Computing, Wearable Computers, Data Management, Data Mashups, Human Data Model, Internet of Things, IoT, Programmable World

ACM Reference Format:

Niko Mäkitalo, Daniel Flores-Martin, Huber Flores, Eemil Lagerspetz, Francois Christophe, Petri Ihantola, Masiar Babazadeh, Pan Hui, Juan Manuel Murillo, Sasu Tarkoma, and Tommi Mikkonen. 2018. Human Data Model: Improving Programmability of Health and Well-Being Data for Enhanced Perception and Interaction. 1, 1 (May 2018), 41 pages. https://doi.org/10.1145/1122445.1122456

1 INTRODUCTION

Today, an increasing number of systems produce personal and intimate data. In digital and virtual worlds human data is produced by our actions in social media and in various types of cloud services. In physical world the data is

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now produced by the ever growing amount of data pumps (wearables, sensors, mobile devices, etc.) next to us, on the network edges, where we and our devices are situated. In this article we call such information that is personal, intimate, or somehow is related to our lives as *human data*.

Human data has plenty of potential for both completely new types of software applications, and for improving already existing applications. This data is especially interesting from a smart healthcare perspective, as the data collectively gathered from our surroundings can be directly related to our well-being [1–3]. In this sense, the well-being of a person lies mainly in the correct monitoring of his or her state of health, both by the person himself or herself, and by health experts. Health centers such as hospitals or private medical centers usually work with data from different sources to create a patient history. Furthermore, this information can be complemented with data from cardiac sensors, glucose, temperature, or any other type that can monitor our health or detect possible anomalies. This implies that the richness of a person's information is conditioned by being able to extract and unify data from heterogeneous sources and process it to favour his or her state of well-being.

The well-being of an individual is also closely related to a person's education and the learning methodologies used. In the field of education, information about people is interesting to enable offering personalised plans or methodologies adapted to the needs or problems that a person may have [4, 5]. There are often cases of people who need special attention due to their abilities, or simply have different needs. This is why the information that can be collected from them through monitoring or activities is undoubtedly of great value in offering them a more adapted and higher quality education. Again, this information is provided by heterogeneous sources, so the correct administration and processing of it will be of vital importance for the education of the person.

At the moment, utilizing this data with the current approaches (e.g., Apple's HealthKit, or Google's Fit) is complex. This is because such platforms mainly provide store and access to data, but are very limited on how this data can be further processed to more meaningful output events to be shared with other users, or provided for end-user applications. In a more broader sense, accessing and using human data requires a wearable (or similar) device sending data to a smartphone or to a back-end service for further processing and use, following the general pattern presented in [6]. Unfortunately, this setting has serious flaws. For instance, Internet companies gathering personal data of their customers can form a privacy nightmare, and transferring data to and from the Cloud is intolerable as the network is about to become a bottleneck in latency-sensitive systems [7, 8]. These can only be fixed by reconsidering the way the vast data is utilized.

In this article we present a new programming model called Human Data Model (HDM). The realization of this model collects data related to our digital and physical lives, and refines it into more abstract sensations. The model offers an API (Application Programming Interface) for accessing and interacting with the now more meaningful data, but the abstractions can also be used for proactively scheduling computer-human interactions. Written in JavaScript, the software implementing the model can be run in almost any computer either inside the browser or using e.g. Node.js, its source code can be freely downloaded from GitHub (https://github.com/HumanDataModel), and the implementation can be used with the existing IoT platforms.

The rest of this article is structured as follows. In Section 2 we present Background and related work for our work to motivate why there is an emerging need for Human Data Model. In Section 3 we present the results of our interviews with healthcare and education sector professionals, as well as the results of our online survey which we conducted to understand professionals' needs regarding Human Data Model. In Section 4, we introduce the Human Data Model at a conceptual level. In Section 5 we provide an insight to the design and implementation of the Human Data Model. In

Section 6, we present an evaluation of the proposed model, based on survey results. Finally, in Section 7, we draw some final conclusions.

2 MOTIVATION: BACKGROUND AND RELATED WORK

Our work has been inspired by the vision of the programmable world [9]. It is manifested in the rapid introduction of wearable gadgets and other monitoring instruments such as mobile phones that can collect data regarding numerous activities us humans are involved in every day. As background and motivation for this work, we provide a brief overview of different designs, their characteristics and typical use cases of collecting and processing human related data. Additionally, we introduce the related work to our Human Data Model approach.

2.1 Overview of data collecting systems for sport activities

In the following, we give an overview of devices dedicated to recording sport activities from four leading manufacturers: Polar, Suunto, Garmin, and FitBit. The list is completed with a review of Google's tools for recording fitness activities: Wear OS and Google Fit APIs. While these are brands, the companies behind them provide APIs that enable accessing data from wearable devices, and for this reason we consider them essential for the proposed Human Data model. The following overview focuses on the analysis of usability and shareability of data from these manufacturers' APIs to third-party software, which are essential factors in our perspective. The pros and cons of these manufacturers can be appreciated in Table 1.

a *Polar:* Data is synchronized to Polar Flow cloud service via mobile phone. Access is provided with AccessLink API [10] to the training and daily activity data. Hence data cannot be directly accessed from the wearable device, and not in real time since the data must first be synchronized to Polar Flow service by the user. Furthermore, the service provides read-only access and any training, health, nor user data cannot be pushed back to the AccessLink. Data files are provided in GPX and TCX file formats and the service provides the following ways to programmatically use the data: Shell, HTTP, Node.JS, Ruby, Python, and Java. The service also provides client applications pull notifications for changed data. All user, training, daily activity, health and physical info data available in Polar Flow is also available through AccessLink API, and also standard FIT format is supported.

b *Suunto* offers a synchronization service and a tool for planning, following up training activity, and registering sleep data [11]. Currently, the Suunto cloud app does not provide any possibility of application development for partners or users. Suunto Cloud API is provided only to companies or organizations that fit the Suunto partner program. As a basic principle, all data within this API is provided in FIT format. Suunto also develops a small System-on-Chip sensor named Movesense for which an open API and SDK (Software Development Kit) are available. Movesense can measure and process motion, heart-rate and body temperature.

c *Garmin* provides open access for smart watch application development through the Connect IQ API [12]. Three options are available differing in what data is made available: Connect API, Health API, or Health SDK. Activity files are available from the Connect API consist of recorded activities such as activity type, GPS route, speed, heart-rate, distance, etc. Files are pushed from Garmin servers after a Garmin user synchronizes the completed activity to Garmin Connect account. The Garmin Health API includes everything that Garmin Connect API provides but additionally delivers all-day health metrics. Whereas the Health API does not enable to control or configure the device, and thus real-time data is not available.

d *FitBit* is the most open device and service in terms of providing sensor data to third party developers. Their Device API provides tools for all device sensors. In principle, all measurements a device is capable of are available through the API [13]. Fitbit enables usage of raw sensor data, but the API also provides methods to make use of processed sensor data. Fitbit also includes a Web API interface for Web or smartphone applications. All data available from the Web API is available on Fitbit servers and can be pulled after Fitbit users first synchronize their watch data to the servers. The Web API offers tools for activity, body weight, food Logging, heart rate, sleep, and user data. All but heart rate data can also be pushed back to Fitbit servers, and thereby can be synchronized to the Fitbit App and other third-party applications as well. Data is provided in TCX and GPX file formats but not in FIT file format.

e *Google:* Wear OS [14] is a lightweight open platform for smart watches. Wear OS apps can be written using Kotlin, Java, and C++ languages, and are similar to other apps that use the Android SDK but differ in design and functionality. Watch apps can also access many standard Android APIs with some limitations. The platform itself makes application development to devices possible. Google Fit API has a broad set of tools for developing health fitness types of applications for Wear OS. It enables access to all device sensors; therefore, raw real-time data is obtainable. Google Fit [15] is an open ecosystem that allows developers to upload fitness data to a central repository where users can access their data from different devices and apps in one location. Google Fit APIs provide Android and REST (Representational State Transfer) APIs to access the Fitness store, as well as a set of APIs that facilitate communication with wearable sensors and their respective recording and storing sessions.

Table 1. Data collecting data for sport activities works.

Data collecting data for sport activities works			
Work	**Description**	**Pros**	**Cons**
Polar [10]	- Plan and track the workouts, the activity and the sleep. Polar provides access to different training and activity data through its API	- Connection with different wearables. - Activity tracker. - Multiple languages to use the API.	- API interaction to Cloud, not directly to wearables. - Not provides data in real-time. - Needs continuous synchronization.
Suunto [11]	- Planning, following up training activity and registering sleep data	- Synchronization service for training and sleep tracking	- Does not provide any possibilities for partners or user - The API Cloud is only available for partner program companies
Garmin [12]	- The Connect IQ system allows third party developers to bring their design and experience to Garmin products	- Multiple options to get data - Detailed recorded usersâĂŹ files	- Health metrics and sleeping data are not available in the API - Real-time data is not available
Fitbit [13]	- It helps to lead a healthier life by controlling the activity, exercise, sleep, nutrition and weight daily	- Is the most opened in terms of providing sensor data to third party developers - API provides tools for all device sensors - All measurements a device is capable of are available through the API - The API also provides methods to make use of processed sensor data	- Web API does not provide access to devices raw data
Google (Wear OS) [14]	- Lightweight open platform for smartwatches	- Multiple languages to develop applications - Google Fit API has a wide set of tools for developing health applications for Wear OS	- Specific APIs depending on the device - Data storage remains in Google servers

A clear motivation for dynamically integrating data from various sources is given by the illustrated variety of services proposed by sport watch manufacturers. Furthermore, when taking into account that the Human Data Model should help to handle all aspects of personal data (i.e., not only sports activities but more generally eHealth measures), this motivation for integrating heterogeneous data becomes even more relevant.

2.2 Human Data gathering for healthcare purposes

Another field in which the acquisition of human data arouses particular interest is the one of healthcare. Currently, there is an extensive collection of sensors designed to perform the acquisition of data such as heart rate monitors, digital scales, oximeters, blood pressure monitors, blood glucose monitors, and so on. These data are usually collected by different organizations, including those corresponding to the health systems of each country, which usually complement the gathered data with others coming from the different medical consultations, diagnoses, medication prescriptions, etc. Some specific systems gathering human data in the health field are reviewed, and their most relevant pros and cons are detailed in Table 2.

a *AMBRO* [16]: A mobile gateway solution for ubiquitous mobile health (m-Health) scenarios, where a Body Sensor Network (BSN) monitors a person in real-time and collects information about their environment. In this sense, the BSN collects information about the location and the heart rate of the user and also detects if he/she has fallen. Each one of these items is mapped to an individual service on the mobile gateway application deployed on a smartphone. The gateway is responsible for sending the information of each service to a caretaker, Intelligent Personal Assistants (IPA).

b *We-care* [17]: A system for the assistance of elderly people that monitors and records vital signs, and provides mechanisms to raise alarms when emergencies are detected. A specifically designed wristband is used to take the vital signs and send them directly to the cloud. The general architecture of the We-Care system consists of three main components. First, the We-Watch bracelet is responsible for monitoring and collecting data from available sensors and sending them securely to the We-Care board of directors. The second component is the We-Care service board, which is responsible for receiving all data collected from We-Watch wristbands and for executing all system services. Finally, the cloud component, where all the services and functionalities are also accessible online, from any place and at any time.

c *Ambient Assisted Living (AAL) architecture* [18]: A system aiming to improve living conditions for elderly people by monitoring their health conditions and giving feedback. This architecture has two main components. The logical component, represented by an Enterprise Service Bus (ESB), is responsible for providing coordination, security, and routing features and whose objective is to ensure interoperability between technologies and heterogeneous data from the sensor network. The second, the hardware component, is a gateway responsible for collecting the data and forwarding them together with instructions to the sensor network.

d *UT-GATE* [19]: A Smart e-Health solution where information related to the patient's health is recorded using sensors on the body. The system architecture includes three main components: a network of medical sensors, which captures data from the body used for the medical treatment and diagnosis. The Smart e-Health Gateway, which supports different communication protocols and receives data from different sub-networks, performs protocol conversion and provides higher-level services and the back-end system, which stores data and provides analytical services.

Table 2. Data gathering for healthcare purpose works

Data gathering for healthcare purpose works			
Work	**Description**	**Pros**	**Cons**
AMBRO [16]	- Automation of tasks in ubiquitous communication scenarios, mainly oriented to healthcare - Interaction with multiple devices	- Static and mobile platforms, depending on the scenario - Automated data collection - Numerous tests performed with location and heart rate data	- Limitations in communication protocols. Mainly use of Bluetooth - Mobile platform limited to Android - Internet connection required to store data
We-care [17]	- Assistance platform for the elderly to monitor and record vital signs - It provides tools to notify in emergency situations	- Affordable solution: low power and cost requirements - Easy integration with IoT networks and standardized protocols - Evaluation tool performed by different types of sensors	- Limited (at this moment) to a small number of sensors - Privacy and security issues to be addressed yet
Ambient Assisted Living Architecture (AAL) [18]	- AAL system for elderly assistance - Continuous monitoring of health status	- Indoor and outdoor GPS location (GPS + BLE) - Data capture from heterogeneous devices in a transparent way - It can trigger events based on collected data	- Limitation for integration with intelligent devices at home - Internet connection required to send data
Smart e-Health Gateway [19]	- Gateway capable of enhancing IoT architectures used for healthcare applications in terms of energy efficiency, performance, reliability or interoperability in healthcare	- Support for different wireless protocols - Local database to store information - Data Encryption	- All process are loaded in the gateway, with the associated overhead - Data deletion when the device is out of storage - Absence of an API that allows the administration of the gateway

The above systems are only a sample of the new proposals interested in human data for health data monitoring and analysis. To improve the state of the art, the development of the Human Data Model should cover aspects that current proposals overlook, such as guaranteeing data integrity, sharing data from different types of sources, and achieving adaptive behavior based on them.

2.3 Human Data processing techniques

Processing techniques come into play when raw data gathered must be processed into bits of useful information regarding the sensor wearer. When placing the focus on digital health, monitoring and sharing generic health data is addressed in [20] with a proposed cloud solution. HealthOS [21] is a development and execution framework for pervasive health applications that has been built to reuse off-the-shelf medical and wellness sensors. HealthOS is able to organize stored data and exposes it through the REST uniform interface. Stream processing frameworks are also currently emerging in this focus of application. For example, the Hadoop-based Intelligent Care System (HICS) [22] proposes an architecture collecting personal medical and health data from sensors to a Big Data collection unit used by Hadoop for analysis. While this approach uses distributed computation with Hadoop for processing data, data is however centralised first into the Big Data collection unit.

Stream processing frameworks help developers to build distributed streaming topologies which gather data from data producers, transform it, and store or visualize it in data consumers. Streaming applications can be used to gather data from sensors and infer behaviors through Complex Event Processing (CEP) [23, 24], a computational approach that takes events from multiple sources and, through analysis, infers patterns or events and responds as quickly as possible. AWARE [25] and mCerebrum [26] are frameworks that can be used to monitor sensing activities by collecting coarse-grained raw data produced by smartphone's sensors. CEP approaches, in general, are closely related to our proposed approach, and many CEP tools can be readily used to process and generate higher abstraction level information. To name some concrete examples, Storm [27] is an open-source distributed real-time computational environment developed by Twitter. Storm can be used to build streaming topologies in Java, offering disconnection recovery and load balancing. Apache Spark [28] is an open-source cluster computing framework that, through the Spark Streaming programming language, lets developers build stream processing applications in the same way they develop batch jobs.

Data streams can also be generated by Body Sensor Networks (BSNs), which can make use of various medical and physiological sensors, including Electro-Cardiogram (ECG), gyroscopes, Electro-Myogram (EMG), accelerometers, Electro-Encephalogram (EEG), or GPS. These sensors can be different, from wearable devices to body implants, providing bio-signal data streams. In [29] authors present state-of-the-art in designing, aggregating, and processing of BSNs' data, and in particular, they analyze issues that sensor networks might face, such as communication, power, stability, privacy, or storage with suggested solutions, which are all highly important factors to consider for a new distributed data processing and programming approach.

Even if stream processing approaches bring the ability to process data as it is generated from events, sharing data between different devices or between software applications remains an issue as applications do not necessarily share the same data schemes.

As a concrete example, applications dedicated to sports activities contain fields dedicated to the user's weight, but sensors associated with these applications are not meant for measuring this criterion. On the other hand, smart scales (e.g., from Withings or FitBit) can measure many different attributes of the human weight, but their applications are not meant to communicate with sport activity applications. As a result, users often end up having several different applications related to their health attributes within the same device. These applications are not able to communicate with each other, and it remains at the responsibility of the user to update different changes in values from one to another application.

Finally, Edge and Fog Computing[1] have increased their popularity recently, as these allow the intelligence disperse from the centralized Cloud to everywhere within the networked environment around the user – network edge devices, smart gateways, and routers, network nodes, and yet part of said intelligence remain in the Cloud. Generally, the notion of the Fog Computing was coined by Cisco to refer to having multiple layers of processing between the device(s) and the Cloud, as opposed to having a single intermediary between the device(s) and the Cloud [31].

The shift in the paradigm even allows deep learning models to be run on smart devices in the fog [32]. A handful of smart devices can outperform a commodity desktop computer or laptop, and two to three can run deep learning-based image classification on a live 60 FPS (frames per second) video stream. Furthermore, in urban environments, a large number of nearby devices (e.g., smart refrigerators, idle processing units of smart TVs, etc.) could be leveraged for data pre-processing nearby with little impact on their users. This would enable large-scale local processing for human data at the location where it is generated, reducing latency and deployment time of new human data-oriented applications.

In the same way as in previous sections and to better understand the technologies analyzed, the Table 3 details the most relevant pros and cons of these technologies regarding our proposal.

[1] It has been repeatedly argued that the distinction between Edge Computing and Fog Computing is not always clear – either Fog Computing is defined similarly to Edge Computing (all computations taking place at the network edges), or regarded as a combination of Cloud Computing, Edge Computing, and all of the options in between [30]. In particular, there is one aspect that may lead to such confusion: mobile phone – the most popular edge device – is actually also a widely used smart gateway. In this paper, we assume the latter interpretation, and refer to all the possible combinations as the fog.

Table 3. Data processing techniques works

Data processing techniques works			
Work	**Description**	**Pros**	**Cons**
HealthOS [21]	- Framework for pervasive health applications - It allows decoupling of applications from devices	- HealthOS organizes the data collected through REST services and exposes it through interfaces and an API - Mechanisms are provided for developers to create health-based applications - Web interface for device management	- Internet connection required for proper functioning between client and server - All data is stored on the server
Hadoop-based Intelligent Care System (HICS) [22]	- Intelligent care system for the exchange of large collaborative contextual data in health care environments	- Data collection from many different heterogeneous devices - Processing and analysis of a large amount of data thanks to Hadoop - Use of low power protocols to connect to the primary medical device	- Data processing is done on remote servers (internet connection required) - Absence of security mechanisms - Data privacy is not guaranteed
Storm [27]	- A real-time fault-tolerant distributed flow data processing system developed by Twitter	- Promotes scalability, is resilient, extensible, efficient and easy to manage - Semantic-based data processing	- Complex system designed for distributed server architectures - Static resource allocation
Health Market Science (https://risk.lexisnexis.com/healthcare/)	- Platform that provides data management as a service in healthcare	- It allows multiple data sources - High security to reduce identity fraud	- Solution not affordable for everyone
Kafka [33]	- Open source multi-platform application developed by the Apache Software Foundation and specialized in data flow processing - High performance and high-power transmission platform used by well-known companies such as Netflix, Microsoft or Airbnb	- High performance solution - It allows horizontal scaling - Fault Tolerance - Easily integrated with REST solutions - Real-time data processing	- Expensive maintenance - Lacks a complete set of data monitoring - Performance in data compression/decompression is reduced
Spark [28]	- Computer system that is based on Hadoop Map Reduce and, mainly, allows to divide or to parallelize the work	- Ease of use - Fast data processing - High integration with Big Data - Large developer community	- Does not have its own file management system - Problems with small data - Does not allow automatic optimization - Not support for real-time data processing (batch processing)
Complex Event Processing [34]	- Methodology that analyze and process event-driven data flows	- Detect behavior patterns based on the data - Applicable in real time - Widely used (IoT, CpS, Finance, Weather prediction, etc)	- Content uncertainty may occur due to data sources - Large memory requirements for processing large volumes of data

2.4 Related Approaches

In comparison to the current approaches, numerous designs share properties related to the approach we are proposing later in this paper, ranging from APIs to full-fledged end-to-end applications, but none of them fully capture all the features we find to be essential for programming human-data applications and interactions. In the following, we address some of the best known related systems, architectures, and frameworks, and point out their key differences to our work. In addition, in Table 4 the most relevant pros and cons about the related systems are detailed.

APIs and programming models: The current APIs of health and wellness services allow accessing data that has been recorded from various wearable and other devices. Examples of API-based systems in digital health include companies such as IBM (Watson Health) and Nokia (Withings). A downside is that in many cases data cannot be accessed in real-time, but instead, it takes at least tens of seconds before it becomes available. For many types of interactions, this is then too late. Furthermore, using such data for implementing scheduling policies may be challenging since the primary driver of these initiatives is the possibility to provide personalized diagnostics and treatments to patients, although Withings and Human API (https://www.humanapi.co/platform) are steps towards human-data interaction capabilities. Similar functions have been realized for the Web in general through the ProgrammableWeb (https://www.programmableweb.com/) service and APIs it specifies and lists for application developers.

In the case of programming models, IFTTT (https://ifttt.com/) is one of the most used approaches for multi-device programming at the moment. The abstractions offered by IFTTT are at a very high level. They can be defined by users with even little technological understanding. At the same time, this simplicity is a hindrance to building more sophisticated systems, where complex conditions need to be met, originating from different sources. IFTTT is very end-user friendly since the "programming" is based on predefined *recipes*, and the end-user sets the parameters for these recipes by defining what should happen when some input is received. IFTTT could thus be used with other platforms (e.g., the one we are proposing in this paper) that provide events (or sensations) serving as inputs for the recipes.

Apple's HealthKit and similar designs composed for the Android platform enable multi-device programming and leveraging health and wellness data in iOS programs. A related but more general initiative is the Wellness Warehouse Engine (https://w2e.fi/), but it only supports a limited number of devices. For a detailed description of challenges related to building such API related systems have been addressed in [35]. Both HealthKit and w2e can complement and provide data for the Human Data Model. For instance, Apple HealthKit provides a mobile-centric solution that makes it easy to access its various data types. On the other hand, w2e provides Cloud-based data integration services and RESTful APIs for accessing wearable device data. We believe, however, that instead of providing such interfaces to the devices, it would become vital to provide means for composing the data from various sources (including the wearable technology) dynamically. For this reason, a JavaScript-based approach would allow running instances on various nodes of the network and then enable injecting data from various sources, like from mobile devices (e.g., by accessing Apple's HealthKit) or Cloud services (e.g., accessing w2e).

Data integrity, quality, and inference: Mobile-centric computing architectures are also aligned with our approach. For example, the People as a Service architecture (PeaaS) [36] stands out for maintaining the integrity of user data captured from their environment by their mobile devices and enabling an adaptive behavior based on that data. More specifically, PeaaS is a mobile-centric computing model to infer the context of smartphone owners and generate their sociological profile. People's sociological profiles gather valuable information to identify moods, trends, or health habits, creating digital projections of their owners. Sociological profiles are stored and shared from the owners' mobile devices. From there, owners can decide with whom and with what purpose to share their sociological profiles. In this way, privacy control is totally in the hands of their owners. However, many human-data application typically requires much more complicated computations to determine concrete actions, whereas applications based on the PeaaS architecture commonly rely on a smaller set of data and associated computations.

On Fog and Edge adoption: Approaches to harness the computational resources of end devices makes it possible to execute resource-intensive computations on the Fog/Edge [32, 37–39]. Complex Event Processing systems can benefit the most from these approaches [34] to process data by avoiding the overhead caused by communication latency. Such a system typically operates in real-time, and everything takes place under the event processing loop. Hence we believe that more fine-grained allocation of responsibilities to different computers is required.

Table 4. Related approaches.

Related approaches			
Work	**Description**	**Pros**	**Cons**
IBM (Watson Health) (https://www.ibm.com/watson-health)	- Building smarter health ecosystems, with simpler processes and continuous development - Increase human experience and improve clinical and operational workflows	- Processing of unstructured data - Ability to work with large volumes of data - Decision Support System - High security and data privacy	- Expensive acquisition and maintenance - Need for intermediate processes in structured data processing
Nokia (Withings) (https://developer.health.nokia.com/api/doc)	- Using real-time data, tracks the extent to which key risk factors for heart disease are related to lifestyle	- Its API allows to create applications for Withings devices and capture their data - The API is for public use	- The API has some limitations (number of requests per minute) - Devices limited to the Withings ecosystem
Human API (https://www.humanapi.co/platform)	- Consumer-controlled health data network	- Multiple data sources: hospitals, medical staff, pharmacies, laboratories, etc. - Multiple types of data: medications, procedures, activities, sleep, diet, etc. - Data security is guaranteed	- Implementation may differ from vendor to vendor - EHR (Electronic Health Record) controlled data and complicated interoperability
Apple's HealthKit (https://developer.apple.com/healthkit/)	- It provides a central repository for health and fitness data on iPhone and Apple Watch. With the user's permission, applications communicate with the HealthKit store to access and share this data	- Very little fragmentation of the Apple ecosystem - Partnership with large companies for physical monitoring (Nike and FitBit) - Capture of important health data such as heart rate, calories, number of steps or sleep control - Detailed data report	- Limited to the Apple ecosystem, for both developers and users - No data management or storage solution included - High competition for data processing (Google)
Wellness Warehouse Engine (w2e) (https://w2e.fi/)	- Tool to collect data related to the user's well-being. Data can be related to activities, measurement or sleep control	- Data querying through the unified REST API for other services - It allows for different data sources	- Compatibility with a few manufacturers - Difficult to reuse data
AWARE [25]	- Open source platform to develop an extensible and reusable platform to capture, infer and generate context on mobile devices	- Scalable and open solution widely adopted and supported by the scientific community - Allows scientists to create their own studies and developers to develop smarter applications - Data can be stored locally or in the cloud	- Aimed mainly at developers. Not suitable for end users to create their own applications - Storage scalability for limited high-speed sensor data
mCerebrum [26]	- Platform that supports high-speed data collection from multiple sensors with real-time evaluation of data quality	- High extensibility by using common data format - Capable of collecting high performance data - Scalability in mission-critical environments	- The cloud component does not automatically support triggering interventions based on previous user data - Difficulty in dynamically changing studies
PeaaS [36]	- Mobile-centric computing model allows sociological profiles of people to be generated, maintained and securely provided to third parties as a service	- Creating sociological profiles of users safely from the context - Local storage of the profiles: only the information is shared with whoever the user wants - The security and integrity of user data is guaranteed	- The types of studies performed on sociological profiles are not specified - Filtering and analyzing this information to infer user characteristics and specificity or to generate relevant information is complex

2.5 Key insights and improvements to prior work

Based on the insights above, we see that systems that have been proposed for human data related processing suffer from two critical shortcomings. On the one hand, some systems are very specific to particular use cases, contexts, or hardware. Consequently, they are a good match for that particular use, and for large enough user base such systems can be profitable and sustainable in the long run. However, to cover the associated development and deployment costs, considerable investments are needed, both for developing the system and for all the required regulatory aspects. Besides, tools and techniques that are needed in the development are often specific to the domain or even the system at hand. On the other hand, numerous systems offer generic services that can be useful when building systems that fall under the domain of health and well-being applications. Unfortunately, such systems are not usually connected to health and well-being data, and, in fact, terms of use may even prevent the use of such data. We see that there is demand for proper approaches that could bridge these seemingly distinct worlds by providing an approach that starts with developers' own willingness when considering the use of wearable devices in applications with specific tools for specific needs.

To meet this demand, new tools are needed to provide application data in real-time and to facilitate access to data for both users and developers so that they can also create applications more simply. Also, data privacy must be guaranteed, which implies that storing data must be done locally in the user's device, and sending it to external servers is to be avoided unless it is strictly necessary. Also, one of the biggest weaknesses detected is that each solution is dependent on the operating system or protocol for which the solution is developed. That is why, in order to address this aspect, a new tool must be independent of the operating system and communication protocols, which would also allow covering a large number of different types of devices and clothing. Although this is not simple, there are methodologies and programming languages that are widely supported by a large number of different devices. In addition, from our point of view, the Internet connection should not be a requirement. This is because many people live in remote areas where connectivity is limited or simply cannot enjoy a quality Internet connection. To achieve this, new tools should not primarily require an Internet connection, and information could be processed on a local device. Therefore, these aspects should be addressed to cover the gap detected in existing solutions. Considering this, the Human Data Model aims to cover these aspects, among some others that will be shown throughout this document.

3 INTERVIEWS AND ONLINE SURVEY

In the following, we report our interviews with healthcare and education professionals, as well as the results of our online survey for people working on healthcare and education fields. The interviews served as a pre-study, and based on the results and ideas that came up to during the discussions with the professionals, we formulated questions for the online survey. The aim of the online study was to collect experiences and ideas from the possible real end-users of the Human Data Model and human-data applications.

3.1 Pre-study: Interviews with Professionals

In Section 2 we introduced many related approaches as well as approaches for collecting human-data to gain understanding if there actually is any need for the Human Data Model that enables using the human data programmatically. To further understand the adaptation and potential obstacles of the use of wearable technologies and human-data application in (Finnish) industry, 15 professionals of well-being and healthcare industries were interviewed. Interest towards technology was broad, but concrete actions seemed to be rare. Non-technical challenges – e.g., business and domain experts lacking of technical skills – were identified in nearly all interviews. In the following, we summarize how the pre-study was implemented and what are the key results.

Goal of the pilot study

The focus areas in this pilot study were Finnish service provider organizations operating in a) well-being and healthcare sectors, and b) education and teaching sectors. Our goal was to better understand the current situation and attitudes in Finnish organizations regarding the use of mobile and wearable technologies. The following research questions guided our research process:

(1) What is the current state of mobile and wearable technology use in Finnish service provider organizations?
(2) What possibilities and issues are there regarding the use of mobile and wearable technology in Finnish service provider organizations?
(3) What are the attitudes towards the possibility of self-programming mobile and wearable technology in Finnish service provider organizations?

Method

Instruments. Data was collected with semi-structured face-to-face interviews with representatives from Finnish service provider organizations. The interview questions consisted of both open-ended and closed-ended questions (options to choose from). The following topics were discussed with each participant:

(1) A brief introduction to what is meant with mobile and wearable technology.
   - The following introduction was given: Mobile and wearable devices offer data collected from user and context, and enable interaction with these collected data. The devices' different sensors enable collection of different data types, such as mechanical, acoustic, biological, optical, and environmental data. Examples of mobile and wearable devices: smartphones, tablets and their applications, smart watches, sport watches, activity bracelets, smart clothing, smart jewelry, and virtual glasses.

(2) Background information and previous experiences with mobile and wearable technology.
(3) How mobile and wearable technology is utilized in your organization?
(4) What are the benefits and challenges of mobile and wearable technology in your organization's field today?
(5) What are the possibilities and issues regarding the utilization of mobile and wearable technology in your field in the future?
(6) In what kind of mobile or wearable technology services would your organization be willing to invest? What are your requirements for such services? (This topic was added after the fifth interview.)
(7) How beneficial would the different data types collected with a help of mobile and wearable technology be for your organization?
   - This included both open ended question and feedback regarding the proposed data types on a Likert scale (Not at all interesting = $1 - 7$ = Very interesting).

(8) What are your thoughts regarding the possibility of self-programming mobile and wearable technology e.g. by creating your own "recipes" (triggers + actions)?
   - An example "recipe" was given before this question.

(9) Give an example of a "recipe" relevant to your field.

Participants. In total 15 participants (7 female, 8 male) were interviewed and included to the analysis. Eight worked in wellness or healthcare sectors and seven in education. However, the teaching of four interviewees also related to healthcare or wellness sectors. All participants were between 35-59 years (M=47.5, SD=7). From the participants, 10 out of 15 rated their knowledge of mobile devices above average (5 or higher), while 6 out of 15 rated the knowledge of wearable devices above average on a scale "None" = $1 - 7$ = "Very good". Table 5 represents the background information for each participant.

Table 5. Participants' background information and self-assessment regarding the knowledge of mobile and wearable devices

ID (E=Education / Teaching, W=Well-being / Healthcare)	Description of occupation	Gender	Age range	Knowledge of mobile devices (None 1-7 Very good)	Knowledge of wearable devices (None 1-7 Very good)
W15	Chief information officer in health care organization	M	31-40	7	5
E07	Teacher of physiotherapy in vocational education college	M	31-40	5	2
W10	Salesperson in well-being services organization	M	31-40	5	2
E01	Teacher of business economics in vocational school	F	41-50	6	2
W11	Work physiology therapist in occupational health organization	F	41-50	4	5
W14	Senior officer for development and services in city service center	F	41-50	5	4
E09	Director of nursing education in vocational education college	F	41-50	4	2
W03	Physical education instructor in city wellness services	F	41-50	5	3
W04	Chief information officer in health care organization	M	41-50	7	7
W05	Chiropractor, entrepreneur	M	41-50	3	5
E13	Director of supportive pedagogy in university	M	41-50	6	3
W08	Director, city service center	F	51-60	7	6
E12	Director of physiotherapy in vocational education college	F	51-60	2	2
E02	Teacher of teacher training in vocational education college	M	51-60	4	3
E06	Senior officer of development in vocational education college	M	51-60	5	5

Process. Participants were recruited first by directly contacting organizations (e.g. health-care companies, city office, welfare institutions and educational establishments) and asking for suitable interviewees for the presented topic. Word-of-mouth technique was utilized in a way that the interviewed participants were asked to recommend other interviewees from their own or other organizations, who might be knowledgeable regarding the study topic.

Before the interviews, an email was sent to each participant, containing a brief introduction to what is meant with mobile and wearable technology, including examples of such technology, and sample questions of the interview topics.

The interviews were conducted by one doctoral student who had several years of experience in conducting interviews. The person was hired for the project specifically to conduct these interviews and online survey because of his good interviewing skills. The interviews were mainly conducted at the participant's work place. One was conducted in a café. All interviews were recorded and transcribed. Each participant received a movie ticket as a compensation.

The researcher who had conducted all the interviews analyzed the qualitative data by coding responses to categories that emerged from the data and summarizing similar responses. Microsoft Excel was used for conducting basic statistical analysis for the quantitative data.

Results

Next, we present the results for each question topic. When relevant, the responses are reported separately from education/teaching (n=7) and wellness/healthcare (n=8) sectors, as divided in Table 5.

How beneficial would the different data types collected with a help of mobile and wearable technology be for your organization?

Table 6 presents a summary of how beneficial the respondents' considered different data types collected with a help of mobile and wearable technology. There was variety in what data was considered important, but it is interesting to see that each data type was considered important by at least one respondent.

Table 6. Participants' background information and self-assessment regarding the knowledge of mobile and wearable devices

Information type	Average	Standard deviation	Min	Max	N
Optical information: Refraction, light wave frequency, brightness, luminance	2.47	1.45	1	6	15
Environmental information: Temperature, humidity	3.27	1.73	1	6	15
Acoustic information: Volume, pitch, frequency	3.50	1.95	1	7	14
Users' input: social media activity (e.g. Twitter, Facebook)	3.57	2.06	1	7	14
Sports activity related measurements	3.60	2.06	1	7	15
Usage data of wearable devices, e.g. usage frequency and time of applications	4.21	2.14	1	7	14
Social context: People physically near you and interaction with them	4.31	1.90	1	7	13
Location (terrain or inside a building) and elevation	4.53	2.31	1	7	15
Safety and surveillance (e.g. when elderly person alone at home)	4.86	2.26	1	7	14
Mechanical information: Position, acceleration, force	5.07	1.88	2	7	15
Health data: Blood sugar, blood pressure, weight	5.29	1.53	2	7	14
Activity data, e.g. steps	5.33	1.49	2	7	15
Users' input: photos, text, videos	5.43	1.95	1	7	14
Sleep and sleep quality	5.73	1.53	2	7	15
Biological information: Heart rate, temperature, neural activity, respiration rate	6.27	1.57	1	7	15

Top five most important data types were:

(1) Biological information: Heart rate, temperature, neural activity, respiration rate
(2) Sleep and sleep quality
(3) Users' input: photos, text, videos
(4) Activity data, e.g. steps
(5) Health data: Blood sugar, blood pressure, weight

What challenges are related to the utilization of mobile and wearable technology in your field?

Top challenges that three or more respondents from service provider organizations mentioned:

(1) **Investing costs vs. benefits** (7 responses). Mobile and wearable technology, especially tailored services, are considered costly and the technology gets outdated at a fast pace. Service providers' customers also need to be convinced to pay for new services offered for them. Budgets in education and public sector can be small, making investing to new technology challenging.
(2) **Technology skills differ within personnel and customers** (7). Younger customers/students and personnel are generally more familiar and comfortable with technology. This challenge is expected to "fix itself" as the current generation retires. However, when designing technology for elderly and people with memory loss diseases, the user group should be carefully considered in the design. Also, including people with knowledge from both the technology and the application area to the decision making process is recommended.

(3) **Attitudes towards technology use and acceptance of new technology** (5). Related to the previous topic, in general, elderly people may have less experience from emerging technology and hence may be more precautions in some cases, the interviewees estimated. Some people can be accustomed to specific ways of working and "be tired" of utilizing new technology, making it challenging to introduce new technology in their work context.

(4) **Making correct choices from the available technology and applications** (4). The sheer number of different options in the market can be overwhelming for those who are responsible of making decisions for new technology. Due the cost of the investments, service providers need reliable information regarding the available technology and its possibilities.

(5) **Reliability of the measured data** (4). If customers use their own devices for measuring different factors, how reliable are the results e.g. for making healthcare related decision? However, from wellness perspective, one of the main goals can be the motivation of the user e.g. towards more active lifestyle, where the exact data readings are not that relevant.

(6) **Privacy issues and data ownership** (4). Often law-related and complex questions that can hinder the implementation of remote mobile and wearable technology related services, e.g. remote surveillance of persons with memory-loss diseases or tracking school students' activities for research purposes.

(7) **No common platform or standards for devices to interact with each other** (3). In school environment, although nearly all students have their own devices, these devices are not necessarily communicating with each other with ease. There are not yet standards for wearable devices on how to connect them to information networks or between each other, in order to find best possible solutions for customers.

(8) **No knowledge of the possibilities with technology** (3). In general, service providers (or their employees) lack the knowledge of the possibilities of the current technology, what data can be collected and how this could be utilized.

What are your thoughts regarding the possibility of self-programming mobile and wearable technology e.g. by creating your own "recipes" (triggers + actions)?

The majority of the respondents (87%) had a very positive attitude towards the possibility of self-programming mobile or wearable technology. Concerns that two respondents brought up were 1) although customers would benefit from such tailored services, there are still too few customers to make the process profitable, and b) making healthcare related decisions based on measured data should not be completely automated as it requires silent knowledge possessed by people who know the customers. Apart from these comments, respondents from various organizations saw that a possibility to easily self-program mobile and wearable services has many potential benefits.

Some of the benefits that the respondents mentioned:

- Saves resources as the same devices could be used with various users
- Different users' different needs could be taken into account more better
- Decreases the work load of healthcare services
- Provides suggestions for the user that could be verified with topic experts
- More personalized support for the user e.g. through positive feedback

3.2 Online Survey

To further understand whether a new programming model could help building new types of human data applications, we conducted an online survey. The survey was targeted to healthcare and education sector professionals, as we see these profiles as potential end-users or persons working on management positions who could have the most insight for an entirely new type of programming model for wearable devices and human data application.

Preparing the survey questions and assessing the results

The questions for the survey were formulated based on the questions and results of the pre-study – 15 interviews with professionals. The team formulating these questions was one professor, one postdoctoral researcher, and one doctoral student who was specially hired because of his years of experience in doing online surveys and interviews. The questions were iterated multiple times by the team and then tested with other members of the department, including in particular personnel from a neighboring research group focusing on human-centered technology. We acknowledge that the way questions are formulated may affect the results, and that it can be challenging to prevent bias entirely. Thus from this survey can provide only early results, and the validity of these results must be considered carefully when used. More studies would be needed for generalized results.

Recruiting the survey participants

The survey participants were selected by sending the survey links via email to healthcare and education organizations. These organizations were partly recommended by the interviewed professionals and partly merely by leveraging the connections that the department had had with other universities, universities of applied sciences, healthcare organizations (public and private), companies working on teaching and education products, etc. The email was sent to secretaries of these organizations who were then asked to distribute the invitation email within their organization to people (e.g., via email lists and sending these directly to relevant people) who had estimated to have 'good knowledge' on wearable technology.

Good knowledge is, of course, subjective. The results were inspected based on the quality of the responses, and it was considered how well the responses align with the self-assessment. Moreover, while good knowledge is important in this kind of survey, it was also interesting to get responses from people who may not have that good knowledge despite their position in the organization, and then consider the reasons. Our interpretation was that there are so few tools and programming aspects for end-users, that many less technical people feel that they do not necessarily have 'good knowledge' on wearables, although the actual reason is that there are no mainstream approaches that the persons even could be aware of.

Demographic information about the participants

We received 304 answers; 55 were professionals working on products and services related to healthcare or well-being. From the participants, 116 were teachers working in research universities or universities of applied sciences. The majority of the participants (159) argued that more accessible programming of human data services would help their companies to create novel services and to establish new businesses. Majority participants (179) indicated that they would be personally interested in experimenting with such a model. Out of these people, 125 participants considered they have good knowledge of wearable devices in general. Many participants (106) considered to have good or excellent knowledge about wearable devices related to their specialized field or profession. Table 7 summarizes the age and gender distribution of the participants. There are many more female than male participants in the survey – 193 female in contrast to 78 males. While this may indicate some gender bias, it also reflects the current gender distribution on the education and healthcare fields, since these fields have traditionally been highly popular among female. Table 8 summarizes the roughly categorized professions and positions of the participants in their organizations. As the results show, the heterogeneity is divers, which was the goal of the survey. Figure 1 summarizes how the participants did self-assess their confidence in using information technology in general.

Table 7. Participants' age and gender distribution.

Gender	20-29	30-39	40-49	50-59	60-69	70-79	No answer
Male	3	20	20	22	11	0	0
Female	14	51	48	50	26	1	1
Other (or do not want to say)	1	1	0	0	0	0	1
Total	18	72	68	72	37	1	2

Table 8. Participants' professions categorized.

Profession	N
Nurse (various levels and positions)	63
Lecturer	27
Researcher (public and private sector)	22
Secretary (various)	18
Teacher	16
Manager (on various levels)	14
Physiotherapist	13
Designer	11
IT and hardware support personnel	11
Professor	11
Doctoral student	10
Therapist / psychologist	10
Medical Doctor	7
Research assistant	4
Teaching coordinator	2
Other	35

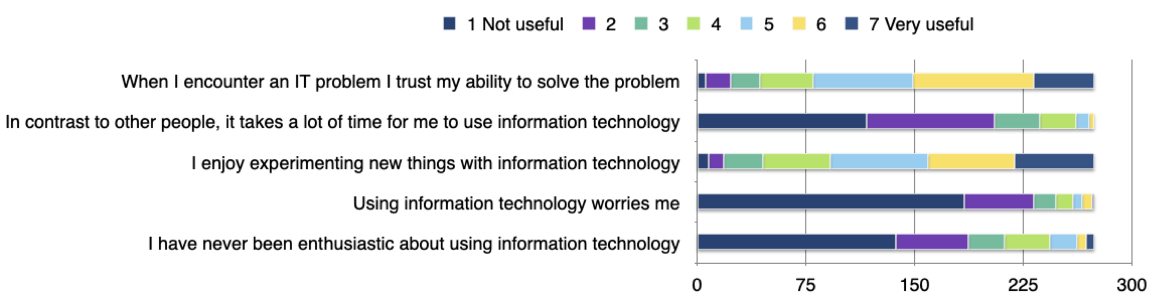

Fig. 1. Participants' self-assessment regarding their self-confidence of using information technology.

Survey Results and Insights

In the following, we analyze the results of the online survey. We also summarize our key interpretation from the survey by listing these at the end of each question as *insights*. Later on, we refer to these insights with their given ID numbers to show the connection between the design and our interpretation of the survey results. The questions asked from the participants include the following main categories:

- what are the backgrounds of the participants,
- how they see the current and future users about the wearable technology,
- what kind of information they would be interested in,
- what would be the services their organizations would most likely be ready to pay, and finally
- if they would be interested in programming new types of services if this would be made easy for them.

Do you use: (a) activity trackers, (b) smartwatches, (c) sports watches, (d) smart clothing and jewelry, and (e) virtual glasses? (270 replies). The most popular devices appear to be sports watches (78), activity trackers (51), and smartwatches (11), which the participants responded to be using every day. From the participants, 19 people answered they had tried using smart clothing or jewelry, but only two participants were using these devices every day. None of the participants was using Virtual glasses every day on their work or leisure time; 2 people answered that they use virtual glasses a couple of times per month; 65 participants replied that they had tried virtual glasses once. Hence virtual glasses, despite all the talk in the media, seem to be relatively rare.

Insight 1. *The most common wearable devices are sports watches and activity trackers, which are hard to program.*

Have you used any other types of wearable devices? In which context? (70 replies). Of the participants, 70 gave some examples of personally using other types of wearable devices, but none of these devices stood out. The following ones were mentioned: brainwave sensing headset (Neurosky MindWave); eye movement tracker (Eye Tribe); smart jewelry (Bellabeats); swimming trackers; smart shoe soles; smart socks (Sensoria); smart running tights; heart rate straps; electrocardiogram (EKG) shirts; EKG-straps; noise indicating shirts; electric sensing cloves; wearable motorbike clothing; professional-level sleep analysis sensors; sports pads and hockey sticks with sensors; diving equipment; and step counters.

Insight 2. *There is a diverse set of mobile/computer-connected wearable devices that are being used for dedicated purposes.*

How are wearable devices utilized in your own organization? If not utilized, why? (240 replies). The most common answer to this question was that the participant didn't know if wearable devices are being used in their organization for professional purposes (47). Based on the other replies, not many organizations at the moment actively use wearable devices for professional purposes. In total, 53 answers mention that wearable devices are being used in their organization in one way or another. The most common way of using these devices is that people use their own devices (22). The wearables are also used in research purposes to some extent (17). Also, some (5) mentioned the use of medical wearable devices, like portable EKG, diabetes, and insulin devices, and some mentioned that these devices are being used for taking care of older people (3) and children (1).

In total, 168 participants answered that wearable technology is not at all used in their organization. There were many reasons given for this: The most common reason was the lack of resources (34), typically referring to the financial ones. The second most common reason was that the answerer or organization didn't see any value in using wearable technology (31). The third most common reason for not using wearables was the lack of knowledge about this technology and its benefits (27). Other common reasons were the lack of suitable devices (16), and that it is not allowed to use any such devices (12) mainly due to hygiene reasons in hospitals. Other reasons mentioned by few was the heterogeneity/amount of wearables devices (3); maintenance is difficult (2); and that the organization management does not see the value (2). From the participants, 31 did not give any specific reason why wearable devices are not used in their organization.

From the software developer perspective, however, it was interesting that only 9 participants mentioned the lack of proper applications as the main reason why their organization was not using wearable technology. We estimate that this may be due to the lack of understanding that such devices could be programmed and leveraged in software applications that would then create value for the users and organizations.

Insight 3. *Wearable technology is not widely used in the organizations of the participating people for professional purposes.*

Insight 4. *Lack of resources seems to be the most common reason for not using wearable technology.*

Insight 5. *Lack of value seems to be the second most common reason for not using wearable technology.*

Insight 6. *Lack of knowledge about the benefits seems to be the third most common reason for not using wearable technology.*

How are wearable devices utilized on your field or profession? (220 replies). In total, 101 participants replied that they are aware that wearable devices are being used in the field they are currently working on. However, the answers about how these devices are being used varied and were very diverse. The most commonly mentioned device seems to be an activity tracker (11) that is not only used for tracking the daily activity levels but also tracking the level of fitness, recovery, or stress, for instance. Other devices that were mentioned several times include Virtual Reality (VR) or Augmented Reality (AR) glasses (8) that were used either in the teaching environment or in research projects for studying the potential usage of these devices in the field. Examples included, for instance, game development and visualizing three-dimensional shapes during mechanic design and modeling processes. From the participants, 4 people mentioned proximity trackers and that such devices were used while working with robots to warn the robot that a human is in close proximity. Other examples individual participants mentioned include various wearable for supervising older people or children, like safety buttons for calling help or GPS tracking devices.

In general, a very common mention was that the use of wearable technology has lately been increasing (13) or that it is expected to increase in the near future (10). From the participants, 64 replied that wearable devices are not being used in the field they are working at the moment, and 56 of these people did not give any specific reason why the devices are not being used (although the reason was not asked). Mainly, the reasons given for not leveraging wearable technology were very similar to the reasons given for the above questions (like money, lack of knowledge, not needed, or hygiene reasons). Of the participants, 53 people replied that they could not tell how wearable devices are being used in their field.

Insight 7. *The ways of using wearable devices for professional purposes vary a lot between the organizations.*

What kind of new opportunities could wearable devices offer for your field or profession in the future? (222 replies). In total, 222 participants gave a broad spectrum of ideas regarding how the wearables could be used in their field in the future. Only in 2 replies people were hopeful that the programmability of the wearable technology would improve in the future, and thus it would be more accessible to them in teaching as well. Various tracking devices were the most commonly mentioned (42). Some of the given examples for the tracking were improving human life, health, and wellness in a proactive manner. For instance, individual participants proposed things such as that the wearable technology "could motivate to stand more in the job that most are done by sitting", or activating students, employees, or patients to improve their well-being, working ergonomics, as well as “improving one’s efficiency”. In general, motivating people to move more with the wearable technology was mentioned several times.

Wearable devices were also proposed for actual healthcare purposes: “Diagnosing children allergies could be done with some wearable activity tracking device, e.g., tracking how well the child sleeps with a specific type of diet”. Participants mentioned diabetes as a future field for wearable technology for observing the glucose levels in near real-time, and one participant suggested that “the wearables could notify about the changes in blood sugar and propose eating something”. Relatively many participants (12) that the rehabilitation process of the patient could be better observed, also remotely supervised (e.g., EKG, blood sugar level, heartbeat, etc.). This was also expected to improve the quality, accuracy, transparency, and cost-effectiveness of the results. From the participants, 4 pointed out that all patient tracking devices that are wireless and other ways easy to use could help to nurse, and thus are very welcome. According to the answers, the wearables could, for instance, help “observing the physical activity of the patient with metabolic syndrome or heart and circulatory system patients”. Many (40) also proposed using the wearable technology for observing the location of their patients (mental illnesses), older people (memory illnesses), or even observing the locations of their students. Other than directly health-related purposes, a common suggestion was to use the wearable technology to give instructions for performing one’s task, which was suggested by 23 people. Of the participants, 17 proposed that this could be done with VR or AR glasses, or with some more traditional wearable devices, like a watch, for instance. One participant suggested that “different types of simulations could be made more realistic with VR glasses”.

Insight 8. *Participants are hopeful that wearable devices would become more comfortable to use in the near future.*

Insight 9. *Participants gave many ideas on how wearable devices could be used in their profession in the future.*

Insight 10. *Observing people and their medical condition near-real time was mentioned to be one of the main opportunities.*

Insight 11. *Proactive services would be desired for improving health and well-being.*

Insight 12. *Real-time instructions would be the desired use case with wearable technology.*

What kind of challenges are related to wearable devices on your field or profession in the future? (215 replies). When asked about the future usage of wearable devices in their field and profession, participants had several concerns. Many of the most common concerns were the same as the concerns leveraging wearable technology today, such as the lack of financial resources (41), the lack of knowledge (20) about the devices and the lack of understanding of how these could be beneficial.

What stood out from the replies were the concerns related to hygiene and keeping these devices clean and sterile (33 mentions). The durability of the devices in professional use was also considered as a key issue, and especially when these devices should be kept clean and how (8). From a financial perspective, 5 people mentioned that it would not then be clear who would be responsible for the expenses of buying, cleaning, and using such technology. From the participants, 9 mentioned that wearable devices get outdated in a relatively short period of time, or that new models are being released almost every year. For this reason, it seemed to worry the participants that a number of different devices and models become even more diverse – requiring even more resources to maintain.

The usability and user experience of the wearable technology was considered to be an issue by many participants (14), as the patients are often older people who often avoid or are even afraid of using such technology. Of the participants, 4 also mentioned that using such devices should be more comfortable so that one would use such devices. Also, battery life was considered to be an issue yet in the future by 2 participants.

Some professionals were also worried about the privacy of the patients because of the confidential data, which they are afraid to become a security risk (14). Also, extracting the data from these devices and leveraging it to something useful was yet considered to be an issue in the future (5). Moreover, it was considered that using Cloud services for storing or analyzing the data would yet become an extra expenditure (2).

Insight 13. *Usability and user experience of wearable technology are significant issues at the moment.*

Insight 14. *Healthcare professionals are concerned about the privacy of their patients.*

Insight 15. *The diversity of devices grows since wearable devices get outdated, and new models emerge often.*

Insight 16. *Extracting the data from the wearable devices is considered to be an issue.*

Insight 17. *The Cloud services for storing and analyzing the data were considered to be too expensive.*

Insight 18. *In general, the professionals seem to agree that decent tools for professional wearable device usage are lacking.*

Estimate how many of your customers or students use wearable devices (i) at the moment, (ii) in two years, and (iii) in five years. (274 replies). We asked the participants to estimate how many of their customers or students use wearable devices at the moment, in two years, and five years. The answers to these questions have been presented in Figure 2. The results indicate that the participants are expecting the wearable technology to become something that most people will be using in five years.

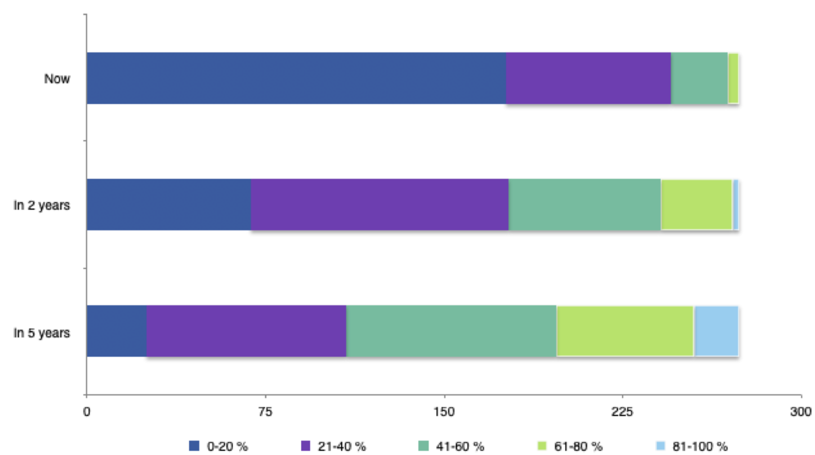

Fig. 2. Estimate how many of your customers or students use wearable devices.

Insight 19. *Wearable technology is expected to become more common in near future.*

Estimate how useful the following information gathered with wearable technology would be in your field or profession. (274 replies). We asked the participants to estimate how useful the following information gathered with wearable technology would be in their field or profession on a scale from 1 (not at all useful) to 7 (very useful):

(1) Biological information: heartbeat (heart rate), skin temperature, nerve system activity, and respiration rate
(2) Blood sugar level, blood pressure, and weight
(3) The amount and quality of sleep
(4) Ongoing activity (e.g., walking, running)
(5) Safety and surveillance related information (for instance when elderly people are home alone)
(6) User-generated stored information: e.g., written text, taken photos and shot videos
(7) Technical environment: Devices in the close proximity and the interaction with them
(8) User or device location on a map
(9) Location inside a building
(10) Sports performance measurements (e.g., heart-rate, distance, speed)
(11) Social environment: People in close proximity and the social interaction with them
(12) Environment information: temperature and humidity
(13) Acoustic information: Volume (e.g., noise level) and pitch/frequency
(14) Mechanical information: position, acceleration and strength
(15) Symbolic location (e.g., "commuting by train", "at work", "home")
(16) Lightning: brightness and color
(17) User's activity and interactions in social media (e.g., Twitter, Facebook, WhatsApp).

The participants estimated the user's activity and interactions in social media (e.g., Twitter, Facebook, WhatsApp) to be the least useful information that could be gathered with wearable technology (3.49). The traditional thinking was repeated with the information type that was considered to be the most useful one: Biological information: heartbeat (heart rate), skin temperature, nerve system activity, and respiration rate. In general, however, the results were similar, varying from 3,49 (least useful) to 5,21 (the most useful), and the average value is 4,41. Thus all the information above was estimated to be useful to some degree, and there were no strong differences regarding various information types.

Insight 20. *All the proposed information types were considered to be interesting for composing new services.*

Insight 21. *Various data sources must be combined to generate meaningful information for professionals.*

Estimate what types of wearable technology related services your organization would be willing to pay? (194 replies). The way how the participants perceived the question varied a lot: Some gave an overall idea or even exact numbers how much their organization would be willing to invest in wearable technology services, while others referred to previous questions and pointed that the organization could be willing to pay from any of such services. From the participants, 30 people estimated that their organization would most likely not be willing to pay from any services. The most common reason mentioned was the lack of financial resources (as already discussed above). From the participants, 39 could not tell if their organization would be willing to pay from any services related to wearable technology.

While the free-form examples were hard to categorize, it seems that the most desired services were related to the health and well-being of the employees, students, and patients. Other typical examples included the well-being services that measure air quality in the office rooms and students'/employees' activity/vitality levels. One participant mentioned that "if the amount of sick leave could be reduced, probably the organization would be willing to pay a few hundred euros per person". Also, safety-related services were mentioned multiple times. For instance, in the care for the elderly, there have already been many services in use that track the older people's movements with various sensors, smart floors, and also people use safety wristbands. The problem mentioned was that the vendors might have changed in the competitive bidding process, and then, if these have been installed in the elderly people's houses, they often are abandoned when issues occur.

Related to well-being and healthcare, very detailed and trustworthy information was desired: "tracking how the movements and body positions change would be something worth to pay for", "observing how vital organs are recovering and functioning", and "Biological information: heartbeat (heart rate), skin temperature, nerve system activity and respiration rate, blood sugar level, blood pressure, weight, the amount and quality of sleep" were desired. One participant estimated that "maybe using some wearable technology could reduce the need for conducting some medical experiments done in laboratories, and for such services the organization or society might be willing to pay for", and that "we would be willing to pay from such services that would help to direct treatments more correctly and more resource-efficiently".

In the education sector, devices that help to supervise the level and ability of the students to learn was mentioned to be very desirable. One participant mentioned that "we would be willing to pay from any services that improve the motivation, commitment, and time management". However, it was also mentioned that this would require that the devices can be customized for various purposes. Virtual learning environments including wearable technology was another education-related technology that the organizations would seem to be most likely to pay.

Insight 22. *The most desired services of the organizations would be related to health and well-being.*

Insight 23. *The organizations want services and information that are detailed and trustworthy.*

Insight 24. *The biggest driver for the organizations for wearable device services would be savings.*

Would you be interested in composing new services or interactions if it would be easy? (274 replies). Based on the responses, it appears that most of the participants (179) would be very interested (willingness ≥ 5) in composing new services or interactions with the wearable technology if this would be made convenient and straightforward for them. The result is very interesting when considering the varying backgrounds of the participants. The results are represented in Figure 3.

Insight 25. *The professionals with varying backgrounds would be interested in programming new services if this would be made easy for them.*

Would the possibility to self-program (that is, implement new service without programming skills) new wearable device products or services improve your organization ability to develop new service concepts? (274 replies). The majority of the people (159) who answered our survey see more accessible programmability of the human data also as an essential tool for creating new business and service concepts. This indicates that people believe in wearable technology and see its value and business potential. The results have been presented in Figure 4.

Insight 26. *Most healthcare and education professionals believe that possibility to self-program wearable devices would improve their organization's ability to build new services.*

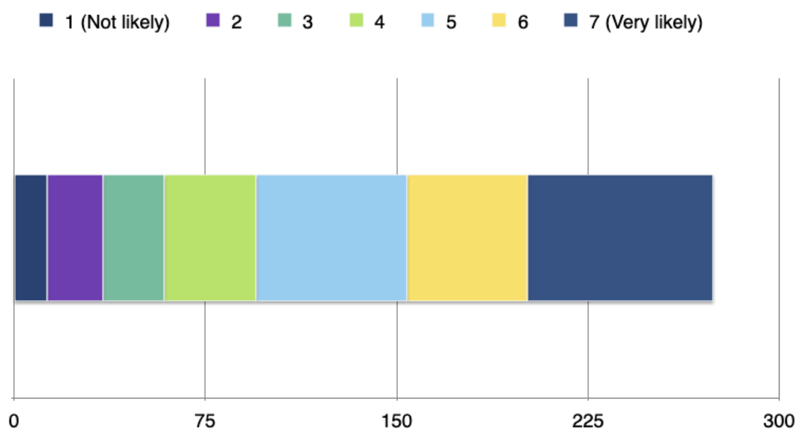

Fig. 3. Professional interest towards defining new services.

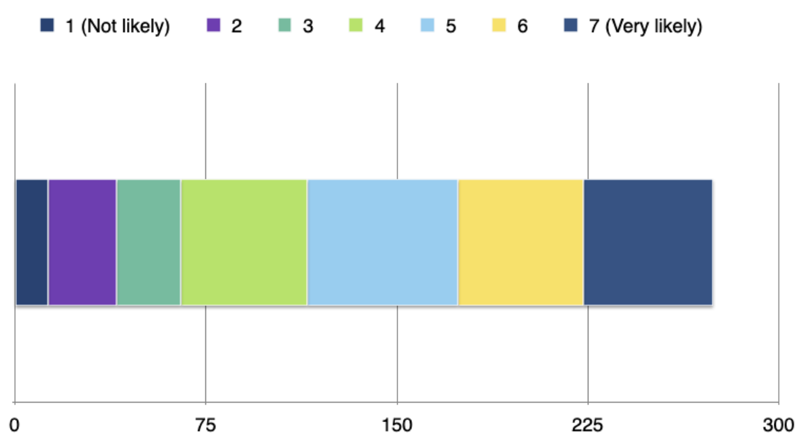

Fig. 4. Estimation if self-programming would improve the participants organization's ability to innovate.

4 QUALITIES OF HUMAN DATA MODEL

According to the results of our online survey, wearable technology is not yet widely used in education and healthcare organizations (Insight 3). The main reason seems to be a lack of resources, including financial resources, and a lack of human resources for studying and applying wearable devices in a professional manner (Insight 4). When good examples of what wearable technology can help to achieve are missing, also lack of value, and lack of knowledge was mentioned to be reasons for not using wearable technology in organizations (Insights 5 and 6). Despite that based on the survey, the wearable technology seems to be leveraged in many organizations, the results of our survey also point out that professionals working on education and healthcare sectors would not only be willing to implement new types of services with wearable devices (Insight 25) but also believe that the possibility to program such services would also improve their organization develop new business concepts (Insight 26). The professionals, however, seem to agree that tools for programming and self-programming are missing (Insight 18).

To leverage the full potential of data produced by humans with their devices at the network edge, and services in the Cloud, the Human Data Model as we propose it has the following qualities:

a *Perception and interaction*,
b *Enabling human–data interaction*,
c *Adaptive behavior and growing new instances*, and
d *Ephemeral sensations and data integrity*

Next, we discuss HDM qualities and explain the motivation behind the design by referring to the insights formed based on the survey.

4.1 Quality of Perception and interaction

Our survey revealed that professionals working on the healthcare and education sectors would be willing to program new types of services and interactions with wearable technology if this would be made easy for them (Insights 25 and 26). Building new services and interactions requires new tools that enable accessing the most recent and up-to-date (Insights 10 and 12), detailed and trustworthy information was considered to play key role (Insight 24).

Perception and interaction go hand-in-hand, and can be considered as a process that consists of *sensation* (input from the world), *anticipation* (what events are expected), *adaptation* (how to react to unforeseen events), and *action* (output to the world) [40, 41]. Altogether, these give a meaning for the interaction, as it has been depicted in Figure 5. Human Data Model uses the term *sensation*, as its main goal is to enable new types of interactions between technology and human and then help to build new types of applications and services.

There are many flavors of perception: perception of persons, of utility, and of information, to name a few. As people interact and communicate more and more in the virtual world, our goal with HDM is to enable collecting raw data from the processes of physical and virtual worlds (Insight 21), and thus help generating the meaningful sensations that are intuitive to use in applications and which enable better perception for new types interactions (Insight 20). Since also social relationships are fundamental in how entities interact in the real world, we made sure in our design that the relationships from the so-called "social world" are reflected in the Human Data Model.

In practice, this means that Human Data Model allows modifying processing capabilities dynamically and flexibly. A developer can then define what types of input data a model instance can sense. Correspondingly, the developer defines how this data is used by that model instance when it receives the data. In essence, on a constrained device this can mean merely preprocessing or filtering the raw data, while on devices with more computing power this can mean combining the data to other data or sensations. Nevertheless, each instance is expected to pass their (pre)processed sensations to other instances.

4.2 Quality of Enabling human–data interaction

Users, with their needs, and devices are different, and hence not all their devices can sense and process all types of data. For instance, the most common wearable devices at the moment can be hard (or impossible) to program (Insight 1). Instead, these devices are typically connected to mobile devices or services and provide APIs for accessing the data. While many approaches aim at unifying the programming by providing APIs to the data collected with wearable devices, the problem yet is that this information may be hard to utilize in practice. Other works, on the other hand, propose solutions for end-user data visualization [42]. One of the critical challenges with wearable technology seems to be usability and user experience (UX). This also came up in our survey as the professionals were hoping that the wearable

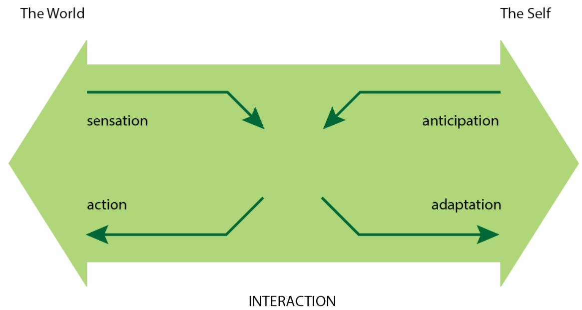

Fig. 5. Perception and interaction depicted. The ideas behind Figure are based on references [40] and [41].

technology would become more comfortable to use (Insight 8) and mention the UX to be one of the key challenges (Insight 13).

For this reason, one key quality of Human Data Model is that it can improve the interaction with human data on various devices, like on a mobile phone, cloud service, or even on a web page and provide easy access to the up-to-date data on applications using it. For example, imagine that when you would log in to a SPA (Single Page Application), this would create a new HDM instance where all your personal data would start synchronizing. You would then grant the SPA access to the data you are are willing to share with it. When you would be finished using the SPA, the HDM instance would terminate, and all your data would vanish from that SPA and the services it is using. This would help to improve the privacy aspect, which was mentioned to be one of the critical challenges of wearable devices (Insight 14).

4.3 Quality of Adaptive behavior and growing new instances

According to our survey, there is already a diverse set of wearable devices (Insight 2) used in different ways in different organizations (Insight 7), and the amount and use of wearable devices are expected to grow in the near future (Insight 19). It would be impossible to gather, transfer, or store all this data from wearables and other devices and services to one location, and it would not even make sense to do so – people constantly move from one location to another, and the results of the processing often needs to be used on the network edges, where people and devices are located [8]. On the other hand, there is a concern regarding the heterogeneity of wearable devices and that these devices get outdated or replaced by new models in a short period (Insight 15), which increase the concerns regarding maintenance costs and resources required for the maintenance (Insights 4 and 17).

An essential quality of Human Data Model is that new instances can quickly be launched and connected to other instances of the same user. This allows new devices to be easily and flexibly connected to Human Data model, and the data gathered with the new and old devices to be treated equally. This is important since the participants of our survey were concerned about extracting the data from various types of devices (Insight 16).

In HDM, connecting new input devices requires that the device with access to the data can get a seed object from the Internet. The seed object, which contains an identifier for the device and various other types of identifiers related to its owner, then has an important purpose of linking the physical, virtual, and social worlds entities and processes. (See an example seed object in Listing 2). This process is called "planting a seed", as after getting the seed, the model begins to "grow", that is, perceive data from physical, digital, and social worlds, as well as from the other instances of the same user.

4.4 Quality of Ephemeral sensations and data integrity

Most desired services were related to the health and well-being of employees, patients, and students (Insight 22). From the given example interactions with wearable technology, three types of features came up (Insight 9): First, some participants seem to be intensely desiring to observe people and their medical condition in real-time (Insight 10). Second, some of the participants desire to implement services that proactively support health and well-being (Insight 11). Third, some of the participants would like to see wearable technology to help to give real-time instructions for their students and patients (Insight 12).

In the real world, the entities around the user may continuously move, and hence the need to interact can be over within a short period of time. To protect the developers from implementing poorly working interactions and false scheduling, we designed Human Data Model to have a quality of ephemeral sensations. This means that the sensation generated and stored by the model becomes invalid within a relatively short period. After this, the sensations are also being removed from the instances to protect the privacy of the user as sensitive information is only available for a predefined period.

5 REALIZATION OF HUMAN DATA MODEL

In the previous Section we described what are the key qualities of Human Data Model and showed the connection between the design and what is desired by the professionals working on healthcare and education sectors. In this Section we describe the current implementation of Human Data Model[2]. The underlying programming model builds on our previous work [43], where an action-oriented programming model based on collective executions is introduced. The main difference of such executions to traditional apps is that collective executions are targeted to run on multiple devices at the same time and that they consider several actors and their preferences simultaneously. Details of the negotiation between parties required for execution, exact scheduling of executions, and other related low-level plumbing are handled inside the programming model so that the developer needs not to consider them while composing the implementation.

As HDM is implemented using JavaScript, we use a simple example Single Page Application (SPA) to illustrate how the model runs in the Fog. In addition, we describe how the model enables injecting raw data from different sources, how it enables generating the sensations, and finally, how it enables accessing the sensations.

5.1 Running Example: School Well-Being Application

To better understand the use of Human Data Model, let us consider the following scenario:

A school psychologist is worried that many university students today suffer from stress. In general, there are two types of stress: distress, which is negative stress and bad for the health, and eustress, which is considered to be positive stress. Based on academic studies, the school psychologist knows that socializing with friends and physical exercise can, on the one hand, relieve the negative distress, and on the other, support the positive eustress. Hence the school psychologist wants a new application for helping the students to leverage the stress for their good.

In the rest of this section, we use this as a motivating example and describe how Human Data Model can be used to build a Single Page Application (SPA).

[2]The development process of Human Data Model is still ongoing. To this end, we welcome any feedback and new collaboration opportunities. All the code is freely available in GitHub at (https://github.com/HumanDataModel).

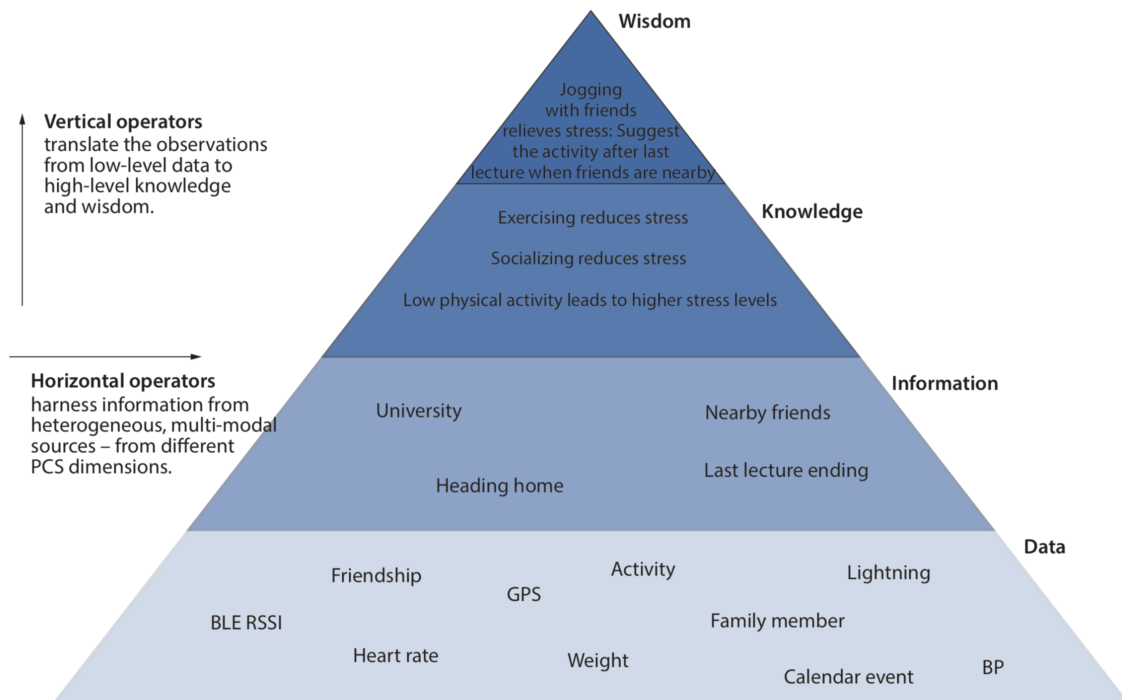

Fig. 6. Horizontal and vertical operations of Human Data Model are based on Physical-Cyber-Social Computing [44, 45].

5.2 Human Data Model – DIKW Operations

Physical-Cyber-Social (PCS) computing was first introduced by Sheth, Anantharam, and Henson in [44] in 2013. Also, others have introduced Cyber-Physical-Social Systems (CPSS), Cyber-Physical-Social (CPS) computing approaches, and a wide range of applications with very similar ideas than the PCS computing approach, as shown by the survey Zeng et al. [46]. Some of the oldest CPSS references are from 2010 to 2011 [47, 48]. PCS computing's main idea is encompassing data, information, and knowledge coming from the physical, cyber, and social (PCS) worlds, and then to integrate, correlate, interpret, and provide human-understandable abstractions that are contextually meaningful [44]. According to the authors, this improves the human experience in computing [45].

Within the PCS computing we can also include existing work with the intervention of human behavior through wearables and sensors. In this sense, in [49] we present a review of some of the most widely used methodologies in the use of wearables for monitoring and supporting people to increase their quality of life and state of well-being. This work includes approaches such as Apple's HealthKit or Google Fit which is a act as reference for the monitoring of human activities. This work is especially interesting as it focuses on some of the most critical challenges for monitoring behavior. In addition, it is motivated by the need to give users, and developers support for the collection and processing of data to obtain contextualized feedback for changing people's behaviour. In [50], authors show the potential of the data flow collected from people through different IoT devices, wearables or smartphones in intelligent environments. This data flow allows us to determine human behavior through Big Data and be able to act accordingly. This work identifies several types of *prosumers* behaviors, understanding behaviors, and changing behaviors where dynamic behaviors of people can be classified. In relation to the classification of behaviors and activities of people, in [51] the authors performed an analysis of current technologies for the fusion of data captured from mobile and wearable devices. This study shows the importance of this type of device for monitoring people and how they contribute to improving their state of well-being. Besides, the main research challenges in the treatment of data linked to behavior and its classification are also mentioned. These works constituted a small sample of how in the PCS there are emerging challenges to analyze the enormous amounts of data, to understand and discover the new models that describe human dynamics and its processing.

PCS computing is built on the Data-Information-Knowledge-Wisdom (DIKW) hierarchy/pyramid with horizontal and vertical operators. On one hand, *horizontal operators* harness information from heterogeneous, multi-modal sources, that is, from different PCS dimensions (e.g., various wearable devices). The *vertical operators*, on the other hand, aims at translating the observations from low-level data to high-level knowledge, and eventually, even wisdom. The sensations with HDM are typically generated with vertical and horizontal operators, characterized in the following:

a Human Data Model enables harvesting data from the social world (e.g., social media services), the digital world (e.g., online tools and services), and the physical world (e.g., wearable devices). This process follows the DIKW (Data–Information–Knowledge–Wisdom) hierarchy/pyramid horizontal operators: HDM allows harnessing data from heterogeneous, multi-modal sources since developers are enabled to implement handlers for new types of raw data inputs. For example, a School Well-being Application might collect raw data with *GPS*, and with wearable devices data about the *activity levels*. *Calendar events*, *Facebook friendship* data, and *Bluetooth RSSI (Received Signal Strength Indicator)* data might be of interest for the application.

b Human Data Model enables translating the raw input data to information, and information to knowledge, and thus follows the DIKW pyramid's vertical operators: HDM supports refining and analyzing the observations from low-level data to a high-level knowledge. The software developers are allowed to program their methods for refining the raw data from the sources they are interested in. On the horizontal level operators, the developers are allowed to combine this data to other data stored in the HDM instance. The School Well-being Application could translate the GPS coordinates to a symbolic location, like the *university* or *home*. It might also translate Bluetooth RSSI values to represent their *owners*, and then combine this data with Facebook friendship data to detect which *friends are nearby*, and finally, combine this data with the symbolic location data in order to detect *which group of friends is at the university*.

c Human Data Model enables observing changes and accessing the sensations (data, information, knowledge, and wisdom) safely and predictably and integrating these into modern software applications. The user (or the owner of the original data) will always be aware of those operations that are allowed to use which data. HDM sensations can help the software programmers implement new types of services, like proactively trigger some interaction. The School Well-being Application could then proactively propose a group of friends to go jogging together immediately after the last lecture of the day and when the friends are gathered together close enough to chat. The application could tell the friends that, according to studies, such as physical activity and socializing, could help them to perform better in their studies and daily life. This process has been depicted in Figure 6.

Table 9. Application Programming Interface of Human Data Model framework.

Programming interface	
addDispatcher()	Used for joining a new connector to Human Data Model framework. Connectors are small libraries that bridge various protocols and connectivity types and a Human Data Model framework instance. After this data via this connectivity can be dispatched to the framework if it has the *input_data_type* added.
addInputHandler()	Adds new *input_data_type* to a Human Data Model framework instance, and a *handler method* for processing immediately after the framework receives the raw input data. The instance only receives data types that are first added with this method.
addSensationGenerator()	Adds new output *sensation* type to Human Data Model framework, and a method for generating such sensations by accessing the data stored inside the model. Parameters are: *sensation type name*, an *array of input data types* that cause the generator to be called, *interval* in seconds for how frequently the generator can be called, and *valid time* value indicating how long the generated sensation is stored in the model. (See Listing 1 for example).
on()	The method is called when sensation gets generated by the model. The parameters are *sensation name* and the *method* that is called when the sensation occurs. Within this scope the contents of the model can be accessed.
Perception of other model instances	
seed_broadcast	The message contains the seed object (see example from Listing 2) containing the identifiers that the Human Data Model framework is permitted to publicly broadcast to other instances.
seed_broadcast_reply	This message is used as a notification, so that the broadcast sender can be sure which instances have received the seed. (Not all the connectivity types and protocols have a built-in support for making sure that the message has been delivered).
Injecting data to the framework with any protocol and connectivity	
input_data	These messages contain the actual raw input data that Human Data Model framework is expected to handle. The message must have key, that is, the *input_data_type*, and then the actual data in JSON format. Additionally, these messages contain authentication key that the software receives from Human Data Model once connected.

5.3 Generating sensations with Human Data Model

Human Data Model framework – the realization of the model – allows deploying *input handlers* and *sensation generators* to its running instances, and, if an instance is connected to the Internet, keeping them up-to-date. These methods refine the raw input data from several sources in virtual, physical, and social worlds to *sensations* that are intuitive for developers. Figure 7 (right-hand side) shows how the a *social proximity set* sensation has been used together with a *symbolic location* sensation which friends are at the university.

Listing 1 contains an example implementation of a sensation generator method that utilizes *bluetooth sensor* and *Facebook friendship* data stored in a model instance. The model then executes this code so that when either of these data

Listing 1. Example implemantation of a sensation generator

```
hdm.addSensationGenerator(
    'social_proximity_set', ['proxemic_devices', 'facebook_friends'], 3, 5,
    function (theModel) {

        var sensation = {
            type: 'social_proximity_set',
            value: {
                friends: {}
            }
        };

        var user;
        for (user in theModel.proxemicUsers) {
            if (theModel.proxemicUsers.hasOwnProperty(user)) {
                if (Object.keys(theModel.facebookFriends).indexOf(user) !== -1) {
                    sensation.value.friends[user] = theModel.facebookFriends[user];
                }
            }
        }
        return sensation;
    }
);
```

sources changes, it calls the generator function defined as a last parameter in the listing. However, to avoid too-frequent calls the third parameter defines how frequently the generator is allowed to be executed. The fourth parameter, on the other hand, defines when the generated sensation becomes invalid. The key methods framework and the messages of API are described in Table 9.

Listing 2. Example seed file for Bod's Human Data Model.

```
var bob = {
    username: "bob",
    identity: "bob@hdm",
    companionUUID: "FB694B90-F49E-4597-8306-171BBA78F844",
    facebookID: "102684690214746",
    devices: {
        "5BF2E050-4730-46DE-B6A7-2C8BE4D9FA36": "bob@iphoneSE",
        "8B034F7B-FA9B-540F-ACF3-88C0CA70C84F": "bob@ibeacon"
    }
};
```

5.4 Executing Human Data Model framework

The heterogeneity of the entities is vast, so we designed the framework so that it is dynamic, flexible, and capable of running on various types of entities. As we noted above, the quality of the model is to be adaptive and grow new instances from a seed file (see Listing 2). In practice, running the Human Data Model framework requires three things.

Firstly, the device gets a seed file. The file is typically fetched from the Human Data Model hub with HTTP protocol. However, it is also possible, for instance, simply copy-paste the file and place it on the device if it lacks Internet connectivity. The purpose of this file is to provide identifiers that connect the social, physical, and digital worlds. For instance, the seed file typically contains Bluetooth UUIDs (Universally Unique Identifiers) that represent specific physical devices. The file also may contain information about the user in the digital world, like identifiers in different services. Finally, the seed file may contain information about the user's social relationships, like Facebook identity, to help getting information about social relationships. This is public information for everyone and can be distributed to all the other interested Human Data Models. An example seed file for Bob's Human Data Model can be seen in Listing 2.

Listing 3. Example JavaScript code for for accessing social proximity graph sensation, and then visualizing this on a Web page. See results from top-right on Figure 7.

```
var currentSocialGraphMD5 = '';
hdm.on('social_proximity_set', function (event) {

    if (currentSocialGraphMD5 !== event.md5 && hdModel.proxemicDevices) {
        currentSocialGraphMD5 = event.md5;

        $('.thegraph').fadeIn();

        updateProximityGraph(
            event.sender,
            hdModel.proxemicDevices
        );

    } else {

        $('.thegraph').fadeOut(5000);
    }
});
```

Secondly, the device needs to be able to execute the JavaScript. Hence the runtime environment of a framework instance can be a web browser, a Node.js server, or a JavaScript framework (e.g., iOS JavaScriptCore framework). JavaScript has quickly become the new de facto technology for implementing prototypes and IoT software. Our main motivations for choosing JavaScript as an implementation language for Human Data Model are the following. Firstly, JavaScript is universal in a sense it runs on almost any type of device. Secondly, JavaScript is dynamic and thus gives the flexibility to extend the language for our purposes. Thirdly, JavaScript is relatively lightweight but yet powerful enough for the computations that are desired from Human Data Model. Finally, JavaScript – while used within Web pages – allows always deploying the latest version of Human Data Model framework to the executing entities, which allows agile development of the model.

Thirdly, the device should also support some connectivity so that the instance can be started smoothly, and can possibly connect to other instances. This also enables other (possibly more constrained) devices to send data to this edge device and hence to the instance. We have previously studied coordination over Bluetooth sockets, Bluetooth Low Energy (BLE), and over the Internet with the HTTP/Comet and Socket.IO (WebSockets) [52] protocols. The used protocol and connectivity type have substantial effect on how the user experiences the interactions. Both local and global communication approaches have their advantages and disadvantages: on the one hand local communication, like the BLE, typically offer stable and fast coordination, but their support among the entities is limited. Global, on the other hand, is supported by the most IoT devices, but the coordination is sensitive for the quality of the Internet connection. However, based on our studies, BLE and Socket.IO fit well for interaction coordination purposes, and the key is to support them both with a communication abstraction. This typically leads to extended star topologies, where some devices with both local and global connectivity act as gateways for the ones that only support local communication.

Now, let's consider how the School Well-being Application could work when the students meet after the class in the university's lobby. In Figure 7, the prototype of the application runs in the Fog: *On top-left*, Bob's HDM instance is running on a Node.js server. *On top-right*, Alice's HDM instance is running inside her Chrome Web-browser on her laptop. These separate instances are aware of each other since Bob and Alice are Facebook friends. *On the bottom*, devices are injecting data into HDM instances. The interconnected instances exchange the generated sensations with each other. The model offers an API for anticipating (publish-subscribe) the sensations and for accessing the data stored in the model, which the School Well-being Application then shows in real-time on a HTML page for illustrating the contents of the model in real-time (*On top-right*). The generated abstract sensations is then be used for scheduling the actions that propose the friends to go jogging together as the school psychologist has defined.

6 EVALUATION

In Section 4 we presented the qualities of Human Data Model and discussed how these qualities were derived from the results of our online survey. In Section 5, we presented the current status of Human Data Model implementation and with an example use case demonstrated how it can be leveraged for in a simple SPA (Single Page Application). In this Section we evaluate how the current implementation meets the qualities of Human Data Model.

6.1 Quality: Perception and Interaction

The programmability appears to be one of the main obstacles for leveraging the wearable device technology and the data these devices provide. For this reason, we have concluded that more intuitive programming concepts are needed. Especially there seems to be needed for easy-to-use approaches for end-user programming and people with limited technical skills. It must be noted, however, that for an average healthcare or education sector, current professional tools for building wearable device software may seem very complicated. Hence a possible threat to the validity of our survey results may be that our survey questions may have affected how positively and enthusiastically the participants see the opportunities of building new types of interactions with the human data.

The primary function of Human Data Model is to enable harnessing, processing, combining, as well as sharing and synchronizing personal data for the use of third-party applications. For this purpose, Human Data Model provides a new programming concept named *sensation*, which we hope to enable a new type of proactive and real-time interaction between humans, devices, and data. In contrast to raw data, the idea is that these new sensations types would be more meaningful for the developers–despite their technical understanding.

When asking the professionals working on healthcare and education sectors, the participants were very interested in all our example sensations types (Insight 20). While all these information types are not currently implemented with Human Data Model, it can, in practice, be used for defining and implementing such information types. In our survey, the professionals were able to compose a rich set of example interactions with the wearable technology, which are leveraging the given example sensation types. Generating such sensations, however, requires combining data from physical, digital, and social worlds' processes.

While professionals were interested in the proposed example sensations, and found the proposed sensations to be useful for defining new services and interactions, it should be noted, however, that in this paper we report the survey results that work only as a pre-study and guidelines for our development work for Human Data Model. Thus more evaluation work in future will be needed on what kind of sensations developers eventually will implement, as well as what kind of sensations the end-users desire, and how developers and end-users will take these implemented sensations.

In the current implementation, Human Data Model supports collecting various types of data from physical, digital, and social worlds. With a single *addInputHandler* method the developer can add a new *input data type* to Human Data Model. As a parameter, the method also takes a function for preprocessing and filtering the raw input data for the new input data type. Similarly, the developer can define a new type of *sensation* to Human Data Model with *addSensationGenerator* method. As a parameter, the method takes the name of the new sensation, an array of input types, and a function for combining these input data types when their values are changed. Both these processes are simple and familiar, for example, from Serverless Computing approaches (e.g., Amazon Lambda), and also resemble

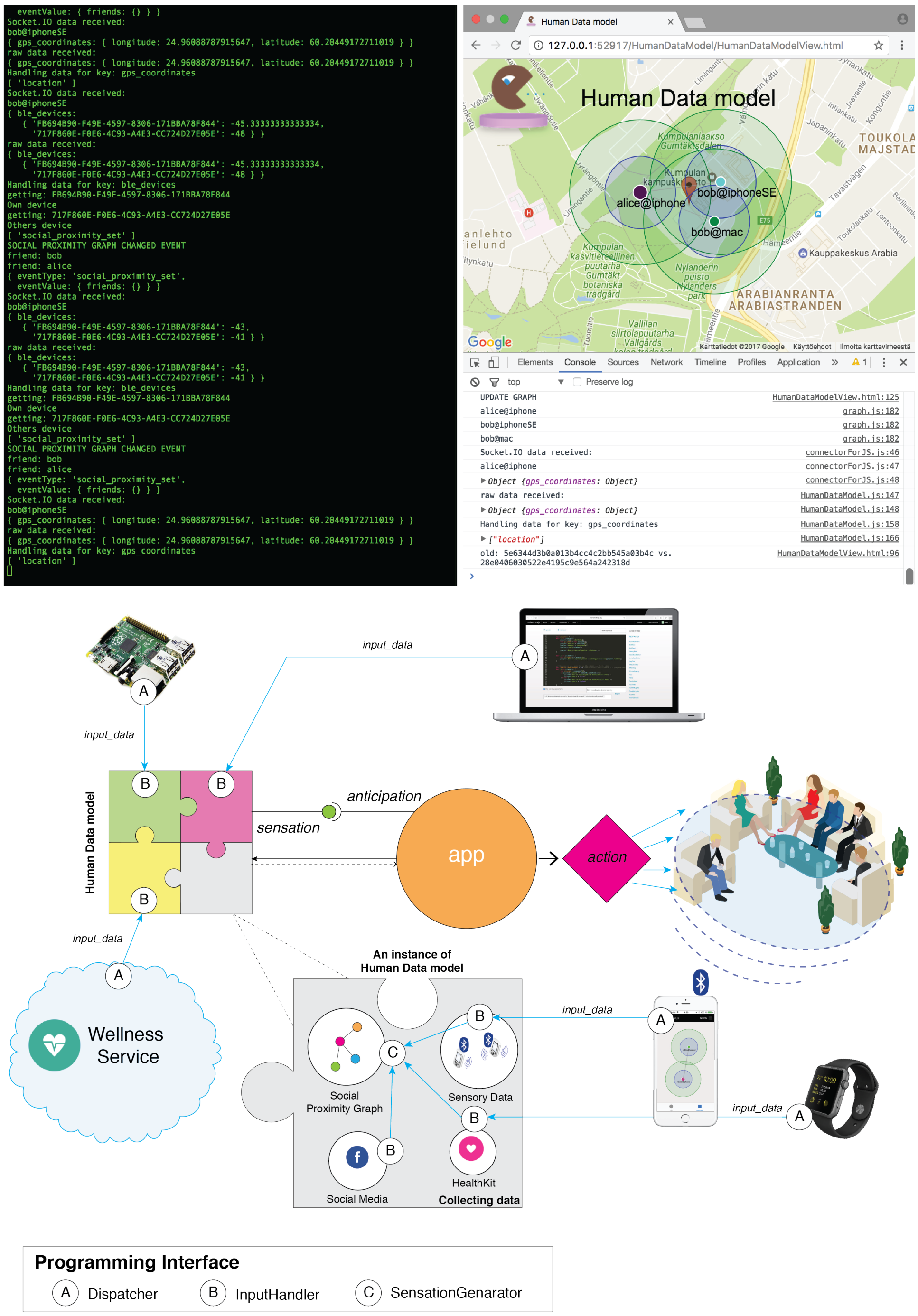

Fig. 7. Human Data Model example operating in the Fog

some JavaScript programming approaches (e.g., React Redux). Following familiar principles makes these concepts intuitive for the developers.

Despite Human Data Model can be used by following familiar principles from other programming models, more evaluation work is needed for studying how well software developers can use the model for harnessing data from social, digital, and physical worlds processes, adding new data sources, and defining new sensations. Moreover, even more, work will be needed to study healthcare and education sector professionals can utilize the developed sensation types and leverage these in their fields.

6.2 Quality: Enabling Human–Data Interaction

One of the critical challenges with wearable technology, in general, is the usability of these devices (Insights 8 and 13) as well as extracting and using the data measured with these devices (Insight 16). From the developer perspective, one key issue of composing new services and interactions with wearable devices was that such devices are hard to program (Insight 1) and that the device heterogeneity causes issues (Insight 2): because of the diversity of wearable devices, there are several ways for programming services with such devices, but yet intuitive tools are lacking (Insight 18). Human Data Model helps to improve the human–data interactions and thus implementing new types of user experiences with the wearable devices and data by offering a single source for accessing the data by offering a single access point to all wearable device data. The model also provides the missing programming concepts for injecting, composing, analyzing, and combing data, and for providing the analyzed data as understandable and meaningful sensations for the applications from unified access points – the human data model instances.

For truly enabling human-data interaction, it is necessary that the model provides means for processing and combining the wearable device data with data from any other sources and observing the changes in near-real time. Human Data Model helps homogenizing how the raw data from different types of devices can be analyzed, combined with other data, and then utilized in the applications. The model also keeps the data up-to-date and makes the old data void. Hence we can conclude that Human Data Model fulfils one of its key requirements, that is, collecting data from various sources (worlds).

From privacy and user-empowerment perspectives, defining with whom the sensations can be shared to could also help improving how the user experiences the data sharing – the user would need to be aware of all different types of raw data and to which various services this raw data is transferred, and further, how these services treat the data and where these services transfer or even sell the user data. Instead, Human Data Model offers sensations as clear abstractions on the human data and its usage, and the user can be allowed to influence which applications or services can access to these sensitive and real-time data abstractions.

For a practical demonstration, we used an example application to show how easy it is to use Human Data Model in a JavaScript-based Single Page Application (SPA). The implemented SPA provided examples of generating a *social proximity graph* that represented which people were situated on the same university area. The example sensation was leveraging different types of data from various sources and combining these into more meaningful abstractions. In the School Well-being example application we were using these sensations for proposing to the group of friends jogging as a physical and socializing activity for reducing distress and/or supporting eustress.

While the demonstration was simple, it showed that a real and working example SPA could be implemented relatively quickly. In the demonstration, the focus was primarily on the data handling and sensation generation since these would be the primary way how most professionals use Human Data Model. Naturally, the abstraction level of the programming concepts depends on who is using the programming model, and what is the goal. While the present implementation of

Human Data Model may be intuitive for a professional software developer, it does not yet provide abstract-enough tools for the most education and healthcare sector professionals for self-programming new types of services, which seems to be desired (Insight 26).

In the future, more work is needed for supporting non-programmers to self-program new interactions and services. We plan to study implementing a graphical tool for combining data sources and applying standard algorithms for the input data. For the end-user developers, there could be a library of algorithms that could be drag and dropped to the editor. Also, in this approach, the more professional and advanced developers would be responsible for implementing the `dispatchers` and possibly also the `input_handlers` that could be used as a possible source for the data.

While studies with real end-users is not in the scope of this paper, we acknowledge that such studies will be essential to validate that the interaction with the human-data benefits and the end-users. Previously, we have evaluated the end-user experiences by conducting studies by arranging controlled tests in a laboratory, and then interviewing the participants afterward. For testing Human Data Model applications in a real context and more significant number of participants, it would be natural to implement applications for example to various public sport events (e.g., marathons and skiing competitions), since many participants are keen to measure their performance and very open for new types of solutions. This interest was also indicated by some of the results of the online survey.

6.3 Quality: Adaptive Behavior and Growing New Instances

Human Data Model enables connecting all types of devices and allowing them to dispatch their data to the model instances. This was considered to be an essential quality of the model since it clearly stood out in the survey, and the participants were worrying that older wearable devices become a burden to maintain (Insight 15). Also, extracting the data from different types of devices was considered to be a big challenge of wearable technology (Insight 16). From these aspects, we can conclude that the Human Data Model should support extracting data from various wearable devices, despite the device design, supported connectivity types, or the device's age. Extracting data requires access to the data source, which is typically an API or a library.

The current implementation of Human Data Model provides a method for adding new data sources with `addDispatcher` method. The method takes a callback function as a parameter, which is called when new data comes to the Human Data Model instance via some communication protocol. Adding other than the above-mentioned connectivity types is certainly possible, but at this point would require implementing new protocol support for the framework.

At present, for communicating with the Human Data Model hub for getting the seed files, the implementation can utilize HTTP and Socket.IO communication protocols. Naturally, it is also possible to extend this implementation to support local distribution of the seed files directly between devices and hence between the model instances. Such ability to locally grow new instances without any Internet connection is worth researching in the future, since not all the environments can provide an Internet connection.

In the online survey, the Cloud-based services were considered to be too expensive for the organizations (Insight 17). The Cloud-based services typically have a monthly subscription or bill based on the used resources, such as the communication as well as computation, and even communicating the results back to the devices. Human Data Model helps to reduce such costs since the computing approach is edge-oriented rather than based on Cloud computing. Human Data Model enables the devices to take responsibility for analyzing, combining and generating meaningful sensations from the raw data all by themselves. These sensations are then synchronized with other devices with running the same user's Human Data Model instances. Many studies have shown how the edge-oriented computation approaches reduce the expenses [7, 8].

Based on the above, in terms of communication, Human Data Model is an improved strategy in contrast to constant streaming of the situational data to the Cloud, as the streaming would drain the battery of the mobile device fast, and would also cause unnecessary consumption of communication resources and computation resources on all the receiving devices. As a concrete example, consider forming the social proximity graph – a very central feature of the example application. Without Human Data Model, the devices would communicate their raw data to a Cloud service. In the environment where five devices are constantly broadcasting such data (BLE UUIDs and RSSI values in JSON format), this means approximately 221 Bytes per every 5 seconds (or the interval chosen by the developer). If the data were updated once in five seconds, this would mean transferring 0.16 MB over an hour by each device, and what is more, per each application, since rarely the streamed data benefits other applications. This quickly makes the Cloud a bottleneck since there can be numerous devices communicating such data.

In Human Data Model, however, the devices themselves combine Facebook and other social media data by directly generating a more meaningful social proximity graph, where the distances between entities are characterized by the physical distance as well as by the social distance. When a change in the graph takes place, Human Data Model generates a sensation, and only such sensations are shared and synchronized between the devices. As an example, if the social proximity graph comprises five devices (the device id together with the social and physical distances), and it changes every 5 seconds, synchronizing this graph over one hour should require the transfer of approximately 0.08 MB of JSON data between the collective executions. Hence, the payload size is about half, and it already contains the necessary information about the distances. Moreover, there rarely is a significant change in distance sensations every 5 seconds, which reduces communication even more.

To conclude the benefits of Human Data Model's edge-oriented computation approach, we can say that it reduces the use of networking resources, may help saving battery in some cases, and may prevent the Cloud from becoming a bottleneck in mission-critical applications. Altogether, these help to improve the adaptability of the system. While typically the issue with Edge computing approaches is the lacking infrastructure support and programming approaches, the Human Data Model is especially targeted to provide such support. For instance, the ability to grow new instance from a seed file is yet experimental, and even at the moment, lacks support for distributing seed files via local device-to-device communication, it yet already seems like a promising approach to allocating new Edge resources for the computations to support human-data interaction.

6.4 Quality: Ephemeral Sensations and Data Integrity

In our survey, the professionals of education and healthcare sectors desired to have up-to-date, real-time, and trustworthy information (Insights 10 and 24). Also, preserving privacy was considered to be important (Insight 14). For this purpose, Human Data Model's concept of sensation was designed to be ephemeral. When the developer defines a new sensation (or input data type), a parameter *valid time* is used for defining how long the generated sensation stays valid, and after which the sensation becomes void and vanishes from the model instances. The sensations also have timestamps, but the idea is that it would not be necessary to use them and that the developer could instead rely on the valid time of the sensation. Presently, however, the current implementation does not take into account if a sensation (child) is built on another sensation (parent), which becomes void before the new sensation. In the future, we plan to study how the lifetime of the sensations should be inherited.

In the future, it should be studied how the ephemeral sensations work in practice to prevent poorly working interactions between the human data and users. In our previous studies, it has become evident that experiments with proactive interactions between users, data, and devices are hard to arrange. The most practical experiments have been controlled experiments in a laboratory setting where the interactions have either been automatically triggered or in the early phases of the research, a researcher has manually triggered the interactions. Despite this, the experiments have give valuable information about how users take these kinds of novel proactive interactions.

In Human Data Model, the sensations are generated only when the value of the sensation changes. Each sensation has an MD5 checksum, which the client applications can use for ensuring that precisely the same sensation has not yet been consumed. Hence, at present, it is on the client application's responsibility to keep track of which sensations it has consumed. In the future, we plan to build this feature directly to Human Data Model and complement it with new methods that call the callback methods of the client application only when sensation has not yet been consumed.

As it has been described, sensations are generated only when their value changes. There are some cases, however, when an application might need to be notified about the existing values stored within Human Data Model instances. How should the applications be notified about the old sensations when a new device connects, and the existing sensations are synchronized on the newly connected model instance. Presently, client applications need to keep track of which sensations they have consumed. In our future studies, we plan to implement a new feature that automatically keeps track of which sensation each client (e.g., device or application) has consumed. Such feature may be prone to the false triggering of interactions, and hence needs to be carefully be tested.

In the current implementation, the sensations are automatically shared among all Human Data Model instances of the owner. Additionally, the developer can programmatically define if the sensation is automatically shared based on a predefined relationship type (e.g., friend, a friend of a friend, family member, colleague, etc.). Although it should be made visible for the users with whom a particular type of sensation is automatically shared, it yet may become problematic in certain situations or with some people. For instance, social relationships (e.g., friendship or being a family member) often mean a different thing for different people, and people like to share different things with their friends, for instance. Moreover, people often are more close with some people within a group (e.g., friends), and may want to limit what is shared with whom also within this group. Similarly, the context typically affects what information people like to share and with whom. Hence in the future, we plan to study more closely end-user programming mechanisms for defining the sharing rules, and how the different contexts should affect sharing the sensations with other people Human Data Model instances.

Additionally, although the predefined lifetime of a sensation does not guarantee the users' privacy, its effect could yet be studied. For instance, if a sensation is shared with friends' devices, it should be analyzed how the sensations can spread and threaten the user's privacy. Naturally, the results depend on the type of sensation, that is, what information it contains, and the persons with whom the user has shared the sensation. Hence such experiments require real-life application implementations for estimating the actual potential threats for privacy.

7 CONCLUSIONS

In this paper, we reported the results of interviews and online survey with professionals of education and healthcare industry. Based on these results, the professionals see the potential of data collected from human activities. Still, leveraging this potential is next to impossible because of the lack of appropriate programming approaches for this purpose. This motivated us to design a new programming model. The design is based on qualities that aim at helping developers implement software that can run at the network edges, where people and devices are located, and where the interactions between them take place. Besides, end-users – the actual application end-users as well professionals working on various domains on healthcare and education – derive numerous benefits from using this developed software, as they can be primarily dedicated to solving a specific problem, such as treating a disease or adapting educational content, which contributes to improving people's well-being and facilitates specific tasks to the professionals in these areas. This is possible thanks to the collection of data from people through heterogeneous sources (physical, cyber, and social worlds) that allow enriching the developed applications and obtaining a higher level of abstraction.

In this article, we demonstrated how abstract sensations can be generated with the Human Data Model framework and how these can be used in a software application. The model builds on collective Human Data Model executions, which simplify developing applications that are run on the Cloud, in the Fog, or at the Edge [43]. At the moment, the framework and the sample code for this are available online for Node.js and iOS/watchOS platforms. These offer a starting point for the developers and show how to connect the model to various Internet services (virtual world), and a Raspberry Pi (physical world).

ACKNOWLEDGEMENTS

The work of N. Mäkitalo was supported by the Academy of Finland (project 328729). The work of D. Flores-Martin was supported by the Spanish Ministry of Science and Innovation through project RTI2018-094591-B-I00 (MCIU/AEI/FEDER, UE) and FPU17/02251 grant, by 4IE+ project (0499_4IE_PLUS_4_E) funded by the Interreg V-A España-Portugal (POCTEP) 2014-2020 program, by the Department of Economy and Infrastructure of the Government of Extremadura (GR18112, IB18030), and by the European Regional Development Fund.

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